INVESTOR SENTIMENT AND INDUSTRY COST OF EQUITY: THE ROLE OF INFORMATION AND PRODUCT MARKET UNIQUENESS

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ABSTRACT

This paper documents a strong negative relationship between investor sentiment, proxied by the Michigan Consumer Sentiment Index, and cost of equity capital, suggesting that the market prices the predominant market-wide sentiment along with other risk factors. Furthermore, we investigate whether certain features of product market affect expected returns through investor perceptions. While we find no significant marginal effect of sentiment in competitive industries (where sales are spread across many firms), we show that the effect of market overreaction is more pronounced for unique industries (measured by the industry's median ratio of selling expense to sales). Finally, we observe an inverse relationship between sentiment and industry average degree of market synchronicity (measured by the magnitude of explained variation in stock returns based on the market model). Specifically, we find that the implied cost of equity for industries with lower average market synchronicity is more (negatively) sensitive to investor sentiment. Our findings are in line with those observed in the behavioural finance literature, which show a more pronounced effect of sentiment on highly volatile stocks.

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CHAPTER 1
INTRODUCTION

The purpose of this paper is to examine whether investor sentiment affects industry cost of equity capital. Do certain industry-specific characteristics, such as degree of concentration, specialized products and information availability, affect the relationship between investor sentiment and cost of equity? Theory presents somewhat conflicting predictions thus an answer to these questions remains purely empirical.

The behavioural hypothesis suggests that when arbitrage is limited, noise-trader sentiment, which is characterised by the behavioural finance literature as being an irrational belief about future cash flows and investment risk that is not based solely on currently available information, may persist in the market, such that assets that are held mainly by individual investors may deviate from their fundamental values for significant periods of time (DeLong et al., 1990). Therefore, sentiment appears to be an omitted risk factor in existing asset pricing models.

Classical finance theory does not take into consideration investor sentiment. Stock prices reflect the discounted value of expected cash flows, and rational investors choose stocks based on their statistical properties, holding diversified mean-variance efficient portfolios (Markowitz, 1959). However, the history of capital markets provides evidence of systematic patterns of mispricing where stocks deviate substantially from their fundamental value. This deviation, on the other hand, cannot be explained by the standard finance theory (Baker and Wurgler, 2007).

Behavioural finance suggests an alternative model of asset pricing built on two basic assumptions. First, investors are subject to sentiment. In each period rational investors and irrational noise traders trade assets based on their respective beliefs, the former's being based on current information, possibly including the expected optimism or pessimism of the latter's. Thus, the equilibrium price reflects the opinion of both types of investors (DeLong et al., 1990).

Second, because of limits to arbitrage, which arise because arbitrageurs are likely to be risk averse and have short time horizons, fluctuating prices are not always forced to fundamental levels (Shleifer and Vishny, 1997). Moreover, the unpredictability of noise traders' sentiment causes additional risk in the market. In other words, betting against not-fully-rational investors is risky and can be costly. If noise traders' sentiment is stochastic and noise traders act in concert, they might cause systematic risk, which cannot be diversified away. Therefore, investor sentiment, like other sources of systematic risk, should be priced in equilibrium (Lee et al., 1991), and if so, it should show up as a significant factor affecting cost of capital. Assets that have greater exposure to noise trader risk are riskier, thus investors holding such assets should expect higher returns on their investment.

Prior work in the field of behavioural finance concentrates mainly on the sentiment-return relation. Baker and Wurgler (2006) find that investor sentiment has significant cross-sectional effect on stock returns. Brown and Cliff (2005) relate sentiment levels directly to stock price deviations from their intrinsic value and find that sentiment can predict security returns. On the contrary, Elton et al. (1998) find that the sentiment index computed from closed-end funds is not a factor in the return generating process. These contradictory results suggest there is something missing in the previous analysis, which may be rooted in i) the indirect approach to measuring sentiment as a separate factor from economic fundamentals, or ii) the use of realized returns as proxies of expected return, which may be a poor proxy of expect returns.

Our study differs from previous research because we test the impact of irrational agents on the cost of equity using a forward-looking proxy of cost of equity instead of relying on average realized returns or using traditional asset pricing models to generate a proxy of expected return. In spite of the extensive work done on studying potentially priced risk factors, finance research has come to the conclusion that estimates of the expected returns based on average realized returns are notoriously noisy and extremely imprecise (Fama and French, 1997). Elton (1999) provides additional arguments that conventional ex post returns provide a poor estimate of expected returns.

Our study makes a contribution to the existing behavioural finance literature by using an alternative and forward looking proxy of cost of equity to test the effect of sentiment on asset pricing. We use the cost of equity generated using accounting based valuation models that estimate an ex ante return required by investors implied in market prices and analysts forecasts and we find a strong robust negative relationship between sentiment, measured by Michigan Consumer Sentiment Index, and cost of equity.

Furthermore, we build on the existing sentiment literature by incorporating product market characteristics into our industry based analysis. We find that product markets affect expected returns through investor perceptions. By doing so our study helps understand the perceived risk associated with the prevailing sentiment in the market and how this perception varies across industries depending on a number of industry characteristics – industry concentration, product market specialization and stock market synchronicity.[1]

The rest of the thesis is organized as follows. Chapter 2 motivates why investor sentiment should affect industry cost of equity and outlines the hypotheses. The hypotheses development is presented in Chapter 3. Chapter 4 defines the regression variables and shows the descriptive statistics. Chapter 5 outlines the main findings of the paper. Chapter 6 provides robustness tests. Chapter 7 concludes the paper.

[1] Firm level market synchronicity is measured using R^2 derived by regressing firm excess returns on the market excess returns. Industry level market synchronicity is the average of firm level R^2 statistics by Fama and French 48 industries. The market model R^2 is predicted to be inversely related to the quality of the information environment (Morck et al., 2000).

CHAPTER 2
RELATED LITERATURE AND MOTIVATION FOR OUR STUDY

2.1. Investor Sentiment

One of the central propositions of modern finance theory is the efficient market hypothesis, which in its simplest formulation states that the current price fully reflects all available information. Investors are assumed to be perfectly rational and are supposed to make investment decisions using all available information. Competition among these rational investors results in an equilibrium in which prices equal the discounted value of future cash flows and only the systematic risk is priced. Even if some investors act irrationally, rational arbitrageurs trade against them and drive prices toward their fundamental values (Fama, 1970).

However, the classical finance theory fails to explain the existence of systematic mispricing in the capital markets. Behavioural finance provides an alternative to the standard model. It argues that financial phenomena can be understood better if we assume that investors are not fully rational. In this setting, asset pricing incorporates not only how expected returns are related to risk but also how returns are affected by investor misvaluation.

2.1.1. Irrational Agents and Mispricing

An individual's investment decisions are affected by a variety of cognitive and emotional biases that may lead them to deviate from fully rational behaviour. Such biases are for example overconfidence, representativeness, conservatism, and informational inferiority complex (Hirshleifer, 2001). Overconfidence is one of the most strongly observed behavioural biases. It has both direct and indirect effects on the way information is processed. The direct effect is that individuals place more weight on information they collect themselves. The indirect effect arises when new information is filtered in a way to maintain the individual's confidence. Thus, investors may systematically overweight information that supports their initial decisions and downplay or ignore information that contradicts them or is inconsistent with their beliefs (Daniel and Titman, 1999).

De Bondt and Thaler (1995) argue that investors are subject to waves of optimism and pessimism that cause prices to fluctuate systematically around their intrinsic values and later exhibit mean reversion. From a psychological point of view, this overreaction to past events is consistent with the behavioural decision theory proposed by Kahneman and Tversky (1973). It states that investors are systematically overconfident in their ability to forecast future prices. As Burton (2003) points out, this provides justification for the investment techniques that are based on a contrarian strategies, such as buying the stocks or portfolios that have been out of favour for long periods of time and avoiding stocks and portfolios that have been highly popular in recent years.

Pepper and Oliver (2006) argue that if deviations of the stock price from its fundamental value persist for a long time, extrapolative expectations can result. In other words, the tendency to expect that price changes will continue in the direction observed recently will proceed. Extrapolative expectations provides a rational for momentum trading with the effect that price fluctuations are likely to continue in one direction. Behavioural finance explains this using representativeness (Tversky and Kahneman, 1974).

If these expectations about persistent imbalance of the intrinsic value are widespread among traders, this can result in a herding behaviour, which may not be outweighed by rational traders who try to restore the price. This excess optimism involves more trading, and subsequently pushes the prices even further away from their fundamental value. The same principle applies to the opposite scenario when excess pessimism drives the stock prices far below their intrinsic value. Through herding and led by extrapolative expectations, noise traders can drive the prices to unrealistically high or low values and generate bubbles or crashes (Hirshleifer, 2001).

Even though psychology-based asset-pricing theory has a great potential for capturing reality, it still lacks quantified models that reflect mispricing. Moreover, it could be misleading to generalize the psychological biases to another context and another set of people, especially when it comes to investors' behaviour in stock markets (Chandra and Sharma, 2010). Real investors and market interactions are too complicated to be summarized by a few biases. Instead, a broader macroeconomic approach should be adopted (Hirshleifer, 2001). Recently, it has been proposed that sentiment affects stock prices (Neal and Wheatley, 1998; Brown and Cliff, 2004, 2005; Baker and Wurgler, 2000, 2006, 2007). However, it's not clear whether this effect derives mainly from expected cash flows or discount rates.

Behavioural finance is based on two assumptions: i) the existence of sentiment among investors and ii) limits to arbitrage. De Long et al. (1990) propose an asset pricing model that incorporates the idea of irrationality. In this model, there are two types of investors: rational investors and noise traders. Rational investors form rational expectations about stock prices, whereas noise traders form their expectations subject to sentiment. Noise traders may falsely believe that they have special information or a better interpretation, which would give them an advantage in the capital market. So when they form their investment strategies, they tend to overestimate asset prices in some periods and underestimate them in others.

DeLong et al. (1990) assume that the sentiment that affects noise traders' asset valuation is stochastic and cannot be completely predicted by the sophisticated investors. This creates additional risk in the market. If the noise traders' sentiments affect many assets and are correlated among different noise traders, then this additional risk cannot be diversified and just as systematic risk it should be priced in equilibrium. In other words, the equilibrium price of assets would reflect the opinions of both rational and irrational traders.

The second assumption is that sophisticated traders cannot eliminate these price deviations from fundamental values by trading against the noise traders as the classical finance theory proposes, because betting against unsophisticated investors is costly and risky. Arbitrageurs tend to be risk averse and usually have limited time horizons (Shleifer and Vishny, 1997). In addition to the fundamental risk, arbitrageurs also encounter the risk that the biased beliefs of irrational traders will persist. For example, if noise traders are driven by pessimism, they drive prices down. So, an arbitrageur buying the asset faces the risk that in the future the price might go down even further subject to growing negative sentiment. Moreover, arbitrageurs do not get the full proceeds of a short sale which means that the hedge is not costless. As a result, they might need to liquidate to obtain funds. If the arbitrageur needs to liquidate her position before the prices return to fundamental values, she suffers a loss. As a result of the limited time horizon and due to risk aversion, arbitrageurs' willingness to take positions against noise traders is limited and mispricing of assets may persist.

In a response to noise traders' investment strategy, it is optimal for the sophisticated traders to exploit the noise traders' irrational misperceptions. Rational traders buy when prices are depressed due to an overly pessimistic attitude of noise traders, and sell when irrational investors' belies are driven by excess optimism. Such a contrarian investment strategy helps balance stock prices towards equilibrium, but because of the limits to arbitrage, prices generally may fail to reach their fundamental value.

2.1.2. Sentiment Proxies

Investor sentiment is not straightforward to measure, and even though there are several proxies, so far there is no consensus about which one provides the best results (Baker and Wurgler, 2007). There are two basic types of market sentiment indices: those that are based on polling or surveying investors and those derived from market data under a theory relating them to sentiment. Some of the most popular proxies used in the behaviour finance literature are as follows:

*Investor Surveys***:**

The survey-based sentiment proxies require that consumers are identified as the individual retail investors that DeLong et al. (1990) refer to as noise traders. There are various indices that indicate the expectations for the market.

Solt and Statman (1988) show that the sentiment measure of Investors' Intelligence is not a useful predictor of stock returns fluctuations. However, Brown and Cliff (2005) provide evidence that investor sentiment using survey data as a proxy for investors' optimism/pessimism affects asset valuation. Fisher and Statman (2003) show that consumer confidence is correlated with other sentiment proxies such as the sentiment measure of the American Association of Individual Investors. Qui and Welch (2006) find that surveys measuring investor sentiment are related to other widespread sentiment proxies as well as market returns. The presence of an irrational element in consumer confidence, measured by the University of Michigan Consumer Sentiment Index, is supported also by Doms and Morin (2004) who show that even after controlling for economic fundamentals, the measures of consumer confidence tend to be influenced more by the tone and volume of the news media rather than actual economic events. Lemmon and Portniaguina (2006) find similar results. They decompose consumer confidence (University of Michigan Consumer Sentiment Index and Conference Board Consumer Confidence Index) into economic fundamentals and investor sentiment and show that the component that accounts for sentiment among investors forecasts the returns of small stocks and stocks with low institutional ownership.

The two most popular measures of consumer confidence are the University of Michigan Consumer Sentiment Index and the Conference Board's Consumer Confidence Index (Doms and Morin, 2004). Although the financial markets and the business community closely follow both indices, the majority of published academic research uses the Michigan Index (Bram and Ludvigson, 1998). There are several reasons that might explain why the University of Michigan

Consumer Sentiment Index is the preferred choice for finance research.

First, it has longer history compared to the Conference Board's Consumer Confidence Index. Second, the University of Michigan Consumer Sentiment Index focuses more on financial conditions, and more specifically on individual's own conditions, whereas the Conference Board survey concentrates more on general macroeconomic environment. Therefore, for the purpose of examining the effect of sentiment in the capital market, the Michigan index seems to be more appropriate. In addition, the surveyed individuals do not overlap, thus the Michigan index tends to pick up some economy-wide sentiment factors rather than the conditions of the respective respondents (Qui and Welch, 2006).

Furthermore, the Michigan Consumer sentiment Index provides information not only about attitudes regarding current financial condition, but also about individual's expectations for one year ahead as well as long-term expectations (5 years ahead). Last but not least, the Michigan survey has intrinsic sampling methods that address certain issues associated with sample selection biases.

Retail Investor Trades:

Lee et al. (1991) identify noise traders or unsophisticated traders with individual investors and show that small stocks are disproportionally held by individuals as opposed to institutional investors. Kumar and Lee (2006) examine the effect of retail trading patterns on comovement in stock returns. They find that trading activities of individual investors contain a common directional component. When some investors are buying/selling stocks, other investors tend also to buy/sell. As investors become more bullish/bearish, these stocks experience higher/lower returns.

Considering these findings, Kumar and Lee (2006) construct sentiment measures for retail investors based on whether they are buying or selling. Kumar and Lee (2006) find that retail investors tend to concentrate their holdings and trading activities in smaller, low price stocks of firms with lower institutional ownership. These are also the type of stocks that are affected by retail investor sentiment to the greatest extent.

Closed-end Fund Discount:

Closed-end funds are investment companies who issue a fixed number of shares, which are then traded on the stock exchange. They are held and traded primarily by individual investors. The closed-end fund discount is the average difference between the net asset values of closed-end fund stocks and their market prices. Lee et al., (1991) show that fluctuations in these discounts are driven by changes in individual investor sentiments.

When noise traders are pessimistic they drive stock prices down, thus, reducing the discount premium. When they are subject to negative sentiment, they undervalue the stock prices and the discount premium goes up. Because of these fluctuations in the discount, arbitrageurs take only limited positions and mispricing persists.

Trading Volume:

Baker and Stein (2004) suggest that if short-selling is constrained, high liquidity can be perceived as a sign that the market is dominated by irrational investors. Those unsophisticated traders add liquidity to the market when they feel optimistic, so higher trading volumes would indicate overvaluation and abnormally low subsequent expected returns for both firm-level and aggregate data.

Dividend Premium:

Baker and Wurgler (2004) define dividend premium as the difference between the average market-to-book ratios of dividend payers and non-dividend payers. Usually, dividend-paying stocks are perceived as less risky with more predictable future cash flows as they are associated with larger and more profitable firms. As a result, the demand for stocks with these characteristics is inversely related to the prevailing investor sentiment.

Initial Public Offerings First-day Returns and Volume:

The IPO market is often viewed as being sensitive to sentiment with high first day returns representing investors' enthusiasm (Loughran et al., 1994). Baker and Wurgler (2007) suggest that IPO volume can also be used as a sentiment proxy. They claim that the underlying demand for initial public offerings is perceived to be extremely sensitive to the prevailing sentiment in the stock market.

Equity Issues over Total New Issues:

The share of equity issues in total equity and debt issues is another measure that captures investors' sentiments. Baker and Wurgler (2000) argue that it shows that rational managers take advantage of temporary mispricing in the stock market by issuing equity when stocks are overpriced. Their study shows that high values of the equity share predict low market returns**.**

Combined Sentiment Index:

A common approach in the literature is to use a combined sentiment index consisting of several of the above mentioned proxies (Baker and Wurgler, 2006). Using a combined sentiment index, Baker and Wurgler (2006) find that investor sentiment has a significant effect on the cross-section of stock prices.

Based on all these findings, we adopt the Michigan Consumer Sentiment Index as our main sentiment proxy.[2] For our robustness tests, we use the Baker and Wurgler (2006) composite index, which is based on the common variation in six underlying market-based proxies of sentiment. These proxies capture sentiment from both the supply (Equity Issues/Total New Issues) and demand sides (IPO volume, Trading Volume, Closed-end Fund Discount) of the capital market and the index is adjusted for the potential lead-lag relationship between supply and demand manifestations of investor overreaction. In addition, the composite index takes into consideration the business cycle and is adjusted for macroeconomic factors.

2.1.3. Sentiment and Firm Characteristics

Baker and Wurgler (2006) argue that mispricing may arise through two distinct channels: i) cross-sectional variation in sentiment, and ii) variation in the difficulty of arbitrage. They define investor sentiment as "the propensity to speculate." Thus, the most vulnerable stocks to noise traders' mispricing are those for which objective valuation is most difficult. Prior studies (e.g. Lee et al., 1991; Baker and Wurgler, 2000) show that such firms are generally characterized as being small, young, unprofitable, non-dividend paying, having high volatility, and being in growing industries. The lack of earning history combined with unlimited growth opportunities encourages unsophisticated investors to speculate with future prices and discourages risk arbitrage by sophisticated investors (Wurgler and Zharavskaya, 2002). Thus, the stocks that are difficult to value are the same ones that are difficult to arbitrage.

When relating sentiment levels to stock mispricing, different studies find contradictory results. For example, Baker and Wurgler (2006) find that investor sentiment has a significant cross-sectional effect on stock returns. Brown and Cliff (2004) relate sentiment levels directly to stock price deviations from its intrinsic value and find that sentiment can predict security returns. On the contrary, Elton et al. (1998) find that the sentiment index computed from closed-end funds is not a factor in the return generating process.

However, when this relationship is explored in the long run (6 to 36 months), the literature finds results that are consistent with the theory. Brown and Cliff (2005) argue that it is more

[2] More details regarding the sampling and the questionnaire are provided in Appendix 2

plausible to view sentiment as a persistent variable. They focus on the long-term reversal of returns to fundamental value because even though, arbitrage forces may eliminate short-term mispricing, they might not hold at longer time horizons. Using Investor Intelligence Indicator as a sentiment proxy, Brown and Cliff (2005) find that excessive optimism leads to periods of market overvaluation which in turn is followed by low cumulative long-run returns as the market price reverts to its intrinsic value.

Neal and Wheatley (1998) study the forecast power of three sentiment proxies: the level of discount on closed-end funds, the ratio of odd-lot sales to purchases and the net mutual fund redemption. They find that net fund redemptions predict the size premium and the difference between small and large firm returns. They observe a positive relationship between discounts and small firms' expected returns but no relationship with large firms' returns. These results are consistent with the investor sentiment hypothesis, which states that small firms' stocks are primarily held by small investors.

2.2. Implied Cost of Capital

Prior research in the field of behavioural finance suggests that models of pricing and expected returns need to incorporate the role of investor sentiment. Thus, sentiment should be systematically related to the cost of equity. Following research in accounting and finance, we use an ex ante valuation approach to estimate the return required by investors based on stock prices and analyst earnings forecasts (Gebhardt et al., 2001, Claus and Thomas, 2001, Botosan and Plumlee, 2005).

2.2.1. Advantage of the Ex Ante Approaches for Estimating the Cost of Equity Capital

Since cost of capital is not directly observable, it is important to find a model that provides an accurate estimate. Some of the most commonly used approaches for estimating cost of capital in financial economics literature are the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) and the arbitrage pricing theory (Ross, 1976). The empirical testing of these models requires measures of expected returns that are generally substituted by an average of realized asset returns. However, as Elton (1999) points out, the historical average is a poor proxy for expected returns.

Fama and French (1997) show some potential problems with cost of capital when using the CAPM and their three-factor pricing model (Fama and French, 1993). They conclude that the uncertainty about the true asset pricing model, combined with imprecision in the estimate of risk loadings and risk premia lead to imprecise estimates of cost of capital at the firm level as well as at the industry level. Fama and French (2002) show that valuation models provide a more precise expected risk premium estimate that tracks fundamentals in a manner suggested by the valuation theory.

In order to obtain an alternative and potentially more accurate measure of the cost of capital, the recent literature suggests a forward-looking approach for estimating the cost of equity capital. The collective evidence from these studies shows that this forward-looking approach deals with many of the flaws of the standard asset pricing models and its main appeal is that it does not rely on noisy realized asset prices (Lee et al., 2010).

2.2.2. Implied Cost of Equity and Sentiment

Prior studies that use ex post return estimates to examine pricing effects of behavioural models find results that contradict the theory on the effect of sentiment on returns. These conflicting empirical findings might be partially due to the choice of realized return as a proxy for expected returns. A model that incorporates investor sentiment will have more credibility if it uses forward looking returns, and has a sound theoretical basis. Therefore the ex ante valuation models provide a promising foundation for incorporating sentiment into asset pricing. This will provide insight into not only how expected returns are related to risk, but also about how required returns are affected by investor misvaluation.

Previous literature uses the ex ante cost of capital estimates to examine a broad range of financial empirical questions. For example, Hail and Leuz (2006) study the effect of legal institutions and securities regulations across 40 countries, Dhaliwal et al. (2006) explore the association between leverage, corporate and personal taxes, and firm's cost if equity capital, and Boubakri et al. (2010) examine the effect of corporate governance on cost of equity to name a few.

As prior literature argues (Dhaliwal et al., 2006; Gode and Mohanram, 2003) accounting based valuation models provide richer context in which to explore the market's perception of risk. In that sense, since in the behavioural framework sentiment is perceived as affecting systematic market wide risk, the forward-looking cost of equity approach is an appropriate choice for our analysis.

Chen (2011) provides evidence that the accounting based cost of equity estimates could be used to explore the behaviour of capital market participants. The author shows that sentiment correlates positively with both expected earnings growth and expected cost of equity capital. Chen (2011) argues that the required rate of return equals the amount of risk times the price of risk, and these two aspects can vary in different directions as investors become more optimistic/pessimistic. For example, if investors are subject to positive sentiment, they tend to overestimate expected growth and underestimate the amount of risk. As far as the price of risk, it might go up as investor sentiment increases. As a result, the increase of the price of risk might surpass the decrease in perceived risk during periods of high sentiment.

Previous research has already suggested that behavioural finance can explain the equity premium puzzle of Mehra and Prescott (1985). Bernatzi and Thaler (1995) show that the equity premium can be partly explained by a cognitive bias called loss aversion, which is the tendency for individuals to be more sensitive to reduction in their levels of wealth than to increases. In other words, investors dislike negative changes in wealth so much that they would accept a much lower expected return to avoid potential losses. Thus, loss averse investors refuse to hold equity securities unless they receive disproportionally large expected returns.

Since equity premium is a notional concept, a possible way to justify any measure is to examine its relationship with variables that affect the firm's risk as perceived by investors (Gode and Mohanram, 2003). In this sense, one of the strengths of the implied cost of equity estimate is that it is correlated with many known risk proxies. Previous literature has found that the implied cost of equity is significantly associated with return volatility, information availability measured by firm size or analyst following, book-to-market ratio, earnings growth, earnings forecast variability, and industry risk premium (Botosan, 1997; Gebhardt et al., 2001; Gode and Mohanram, 2003).

Previous studies have also found relations with a number of market mispricing anomalies. Stocks with higher past realized returns tend to earn higher subsequent returns. If price momentum is a risk proxy, then high momentum stocks should have a high implied risk premium (Gebhardt et al., 2001). However, momentum is a phenomenon often related to investor sentiment. Another such example is turnover. High turnover firms should have lower ex ante implied risk premia (Gebhardt et al., 2001). On the other hand, Baker and Stein (2004) suggest that liquidity can be used as a sentiment proxy. Irrational traders add liquidity to the market when they feel optimistic; therefore higher trading volumes are perceived as a signal of overvaluation.

Finally, if market prices reflect fundamental value, the implied cost of equity and ex post realized returns should be positively correlated especially over longer horizons (Frankel and Lee, 1998). Likewise, Brown and Cliff (2005) show that in the long run we can observe the sentiment – return relationship.

This empirical evidence reinforces the previously discusses theoretical argument that sentiment is an omitted risk factor in asset pricing models.

2.2.3. Analyst Forecasts

One of the potential strengths of the ex ante valuation models is the use of analysts' forward-looking information, which is perceived to be a more precise measure of market expectations compared to the average of realized returns. It is assumed that the stock market efficiently incorporates analysts' forecasts into stock prices and that analysts make unbiased forecasts (Claus and Thomas, 2001).

Prior research has linked investor's different cognitive biases as well as the prevailing investor sentiment to analysts' forecast (Guay et al., 2003) but yet there is no direct test of the effect of sentiment on the derived cost of equity estimates from these forecasts.

Lys and Sohn (1990) show that analyst forecasts fail to incorporate new information in a timely manner. Consistent with this finding, Guay et al. (2003) argue that the sluggishness of analysts with respect to information in past stock prices results in a predictable error in the implied cost of capital. It is well established in the literature that security analysts are prone to overreact given the available information. De Bondt and Thaler (1990) show that forecasts are too optimistic and too extreme, and these results are stronger for longer forecast horizons. Claus and Thomas (2001) find similar results. Their study shows evidence of a "systematic optimism bias" in the earnings forecasts that increases with the forecast horizon. In addition, analysts tend to be more optimistic for firms with low book-to-market ratios, low earnings-to-price ratios, and high levels of capital expenditures (Dechow et al., 1996). Similarly, Guay et al. (2003) find that analysts' forecasts are more optimistic for small firms and growth firms. La Porta (1996) as well as Dechow et al. (1996) show that stock prices naively incorporate analyst's long-term earnings growth forecasts even though these forecasts are systematically biased. If sophisticated traders, such as analysts, face problems with processing stock market information and give forecasts subject to heuristics, then we would expect that the investment strategies of noise traders would be even more influenced by overreactions.

On the other hand, the excess optimism observed in analyst forecasts might also be a result of agency problems. That is, optimistic forecasts are preferable for brokerage firms, which generally make more buy recommendations than sell recommendations (De Bondt and Thaler, 1990). Moreover, analysts derive some of their expertise from the executives of the companies they follow, which might motivate analysts to present the firm in a favourable light (Easterwood and Nutt, 1999). Cowen et al. (2006) find that trading incentives, firm status and types of clients are among the factors that contribute the most for excess optimism among analysts. Therefore, higher optimism is distinct to brokerage firms that provide retail services. Moreover, sell-side analysts may stop issuing reports about stocks they don't find attractive, which also contributes to their general optimism.

On the contrary, other studies find that analysts systematically underreact to prior earnings information (Abarbanell and Benrad, 1992; Lys and Sohn, 1990). This tendency for analysts to underreact to new information can be explained by the psychology of decision making, which claims that individuals have bounded rationality and tend to underreact to new information that conflicts with their initial beliefs (Barberis et al., 1998). Gleason and Lee (2003) argue that as a result of analysts' partial adjustment, their past revision actually predicts future forecast errors.

As opposed to both of these streams of research, Easterwood and Nutt (1999) argue that analysts react differently depending on the nature of the earnings information. More precisely, they underreact to negative information and overreact to positive information, which suggests that analysts are systematically optimistic.

Ding et al. (2004) use prospect theory to explain stock market reactions resulting from an earnings surprise. They find that, due to investor loss aversion, stock returns react strongly to positive earnings surprises, whereas negative earnings surprises have no significant influence on returns. In other words, investors are reluctant to realize their losses during negative earnings surprise. Ding et al. (2004) also find that analyst forecasts tend to be accurate during positive earnings growth and highly optimistic during negative earnings growth, which is associated with the presence of positive investor sentiment (proxied by the American Association of Individual Investors' Sentiment Survey).

If analysts have a reason to be optimistic in their forecasts and their optimism bias is entirely explained by economic incentives, this would mean that they are not affected by sentiment. However, as pointed out by Cowen et al. (2006) sell side analyst forecasts are aimed mainly at retail investors who are prone to irrational trading to the greatest extent. If the same individual investors, who are identified with the noise traders in the stock market, follow overly optimistic/pessimistic forecasts and recommendations, they might transfer this overreaction to the market and cause additional risk. This gives us another reason to explore the association between sentiment and cost of equity estimates derived from market price and analysts' forecasts and expand the literature on the effect of behavioural factors on the analysts' forecasts.

CHAPTER 3
HYPOTHESES

Our choice of industries as a unit of analysis is mainly motivated by Moskowitz and Grinblatt (1999, p.1288) who argue that "*firms within an industry tend to be highly correlated; they operate in the same regulatory environment, exhibit similar behavior in the corporate finance area, are similarly sensitive to macroeconomic shocks, and are exposed to similar supply and demand fluctuations.*" They find strong evidence that industry portfolios exhibit significant momentum even after controlling for size, book-to-market ratio, individual stock momentum, the cross-sectional dispersion in mean returns and potential microstructure influences.

If we relate these findings to the behavioural finance theories, the pronounced industry momentum effect could be explained by investor cognitive biases such as overconfidence and self-attribution (Daniel and Titman, 1999). As previously discussed, the individual stocks momentum anomaly has already been broadly explored and linked to investors bounded rationality (Barberis et al., 1998; Jegadeesh and Titman, 1993; Pepper and Oliver, 2006). Given the results that industry momentum is never subsumed by individual stock momentum, slow information diffusion and extrapolative expectations hold not only at firm level but also at industry level, causing industry mispricing (Moskowitz and Grinblatt, 1999).

Since investors face certain challenges in processing new information, they tend to group assets into categories and, thus, simplify their portfolio decisions (Barberis and Shleifer, 2003). Because of this bounded rationality, noise traders allocate funds at the level of some particular categories or habitats rather than at the individual asset level because of transaction costs, trading restrictions or lack of information. In this instance, correlated sentiment among noise traders creates herding behaviour (Barberis et al., 2005). Sentiment literature has already explored the effect of unsophisticated trading activities on portfolios based on size and growth opportunities. However, categorization based on industry characteristics has yet to be explored.

An industry-based analysis is also motivated by the fact that the majority of Wall Street analysts who provide earnings forecasts and buy and sell recommendations specialize by industry. Boni and Womack (2005) show that industry aggregate analyst recommendations provide a better understanding of market efficiency and price momentum. For example, aggregate recommendation across all analysts by industry provides better signals for future returns compared to a non-industry approach. Another finding suggests that industry average recommendations (upgrades/downgrades) are strongly influenced by preceding industry level returns suggesting that analysts take into account industry returns when they revise their opinions about the stocks they follow.

Using industry averages of cost of equity estimates could mitigate some of the concerns associated with analysts' forecast sluggishness and excess optimism. For example, even if analysts try to present some firms in a favourable light because of certain incentives, the effect of these optimistic forecasts could be reduced by taking industry averages. Furthermore, valuation models used in the estimation of cost of equity rely on assumptions about different inputs, which could increase the likelihood of spurious results. Taking an average estimate over four different models is a common approach to minimize such spuriousness (Hail and Leuz, 2006; Dhaliwal et al., 2006). In that sense, using an industry average of cost of equity could further help avoid spurious estimates.

Based on the literature discussed so far, we find both theoretical arguments as well as empirical evidence that suggest retail investor sentiment is an omitted risk factor in the asset pricing models. However, whether this effect derives from expected cash flows or discount rates remains largely unexplored. We test whether sentiment affects the required rate of return by using forward looking estimates of expect returns (i.e. implied cost of equity).

Chen (2011) examines the relationship between investor sentiment and expected cost of equity capital measured with ex-ante valuation models. The author finds a positive correlation between sentiment and cost of equity by studying two distinct channels through which sentiment affects asset valuation: earnings growth and required rate of return. Chen (2011) conducts his tests using firm level data. As opposed to his study, we concentrate on the aggregate effect of sentiment on industry-average cost of equity and we form our hypothesis based on the premise that given the annual frequency of our data, patterns of *correction* of mispricing are easier to detect rather than the mispricing itself.

If sentiment indeed cannot be diversified away because of limits to arbitrage, then it should be priced and therefore, sentiment should negatively affect the industry average implied risk premium.

H1: Investor sentiment is negatively related to industry cost of equity.

In other words, as noise traders become more pessimistic, or when they are driven by negative sentiment, they require higher rates of return on their investments, since they believe that there is more risk involved. If rational arbitrageurs cannot eliminate their effects because of limits to arbitrage, the cost of equity should incorporate the pricing of both rational and irrational traders. On the other hand, if noise traders are overly optimistic, they would overvalue certain firms. This in turn, would result in a lower cost of equity once the mispricing is corrected.

Adopting an industry based approach requires taking into account the industry market structure and its asset pricing applications. Building on industrial organization theory, Hou and Robinson (2006) argue that the structure of its product market affects a firm's operational decisions, which in turn can have an impact on the riskiness of the firm's cash flows. Therefore, the structure of the product market may affect the firm's stock return. Hou and Robinson (2006) shows that firms in more competitive industries earn higher returns even after controlling for size, book-to-market equity, momentum and other factors. These results hold for both industry and firm level analysis.

Hou and Robinson (2006) propose two channels through which product market structure can affect asset prices. In their paper they focus on the risk-based channel, linking industry concentration to stock returns through innovation and barriers to entry. Creative destruction (Schumpeter, 1912) predicts that firms that engage in more innovative activities are riskier and have higher returns. A more recent study of Knott and Posen (2003) finds empirical evidence that innovation increases with the degree of industry competition. On the other hand, Bain (1954) argues that concentrated industries are more profitable and face less distress risk. Hou and Robinson (2006) find supportive evidence for both risk determinants through which product market structure affects stock returns. They show that firms in more concentrated industries are less risky and earn lower returns because they engage in less innovative activities and are better insulated from undiversifiable aggregate demand shocks.

The other potential channel through which the structure of the product market could affect cash flow risk is indirectly through investor perceptions. Hou and Robinson (2006) suggest that it could be behavioural bias that causes investors to undervalue firms in more competitive industries resulting in higher ex post returns. This is the channel we will focus on and test whether investor sentiment effect varies with industry concentration.

The link between stock market performance and firms' competitive environment is also supported by Gaspar and Massa (2006). They find that firms with strong market power have lower idiosyncratic volatility. The proposed arguments for this finding are that firms operating in concentrated industries have lower information uncertainty for investors, hence, lower volatility. In addition, market power could be used as a hedging instrument and therefore leads to lower idiosyncratic fluctuations.

Irvine and Pontiff (2009) provide further evidence for the relationship between the intensity of product market competition and stock returns. Their international study shows that the recent upward trend in increasing idiosyncratic volatility in the financial markets is attributable to an increasing competitive market environment. In addition, this study incorporates the information availability measure, based on market model returns R^2s, arguing that information opacity affects country's business environment, which in turn has effect on stock returns. They also observe that after deregulation takes place in certain industries, increases in competition coincides with increases in idiosyncratic risk.

As an extension of these studies, Peress (2010) explores more closely the link between firms' market power in the product market and their stocks in a perfectly competitive stock market. Higher market power stimulates trading, including that of insiders who presumably have privileged information, and enhances the information incorporated in stock prices. Thus, earnings' forecasts for these firms are less dispersed, stock liquidity is increased, volatility of profits and stock returns is lowered, and these firms have lower expected returns. In other words, product market imperfection, or monopoly power, is not transferred to the financial markets. Instead, market power helps mitigate information and allocation efficiency (Peress, 2010).

Gaspar and Massa (2006) find that the high variability of analyst earnings forecasts about firms operating in competitive industries indicates that these firms are easier to speculate with since objective valuation is more difficult compared to firms with greater market power. Furthermore, Lee et al. (1991) show that the stocks most vulnerable to noise traders mispricing are those with high volatility. Therefore, we expect that sentiment should have a stronger negative effect for more competitive industries.

H2: The negative relationship between cost of equity and investor sentiment is stronger for firms in industries with lower degree of concentration.

Aspara and Tikkanen (2008) argue that the same individual investors who engage in trading stocks also engage in product consumption. Thus, individuals' attitudes toward certain products are transferred over to the stock market. For example, consumers could have a positive attitude towards the idea of social responsibility, therefore consuming products by companies with such practices and respectively investing in the same companies. Aspara and Tikkanen (2008) also propose that an individual's positive attitude toward a company positively influences his optimism and overconfidence in forming expectations about earnings and price of the company, which in turn influences his tendency to buy/hold stocks.

To test this, we consider industries with products that don't have direct substitutes or switching to a substitute would impose extra costs to the consumers (either directly or through brand loyalty). Thus, industries with a high level of product uniqueness as measured by the ratio of selling expenses to sales (Wessels and Titman, 1988) should be affected by investor sentiment to a greater extent.

H3: The impact of investor sentiment on cost of equity is stronger for industries with greater product uniqueness.

Lastly, we look into the relationship between information availability and the effect of investor sentiment on industry cost of equity. Intuitively, industries with more information asymmetry between firms and investors should be more susceptible to the prevailing sentiment in the market as objective valuation is not straightforward. We follow a recent stream of literature (e.g. Morck et al., 2000; Durnev et al., 2003) that nominates market synchronicity, measured by the magnitude of explained variation in stock returns based on the market model, as a proxy for information availability.

Grossman and Stiglitz (1980) argue that since obtaining information is costly, informed trading would be more prevalent in stocks for which private information about fundamentals is cheaper. Thus, more intense informed trading leads to "more informative pricing." In other words, firm-specific variation, as measured by the R^2 statistic from regressing the market model or a similar asset pricing model, is related to informativeness of the stock prices. Roll (1988) provides empirical support that arbitrageurs' trading is especially important for the capitalization of firm-specific information, and idiosyncratic volatility is not associated with public information releases. However, Roll's (1988) overall conclusion is that high firm-specific price fluctuations could be a sign of either more information due to active trading by informed arbitrageurs, or it could be associated with less information due to noise traders.

Subsequent researchers favour the interpretation that firm-specific volatility refers to a better information environment and market efficiency. Morck et al. (2000) give further evidence that the R^2 statistic obtained from the market model is an indicator of information quality. They find less synchronicity across returns by firms in countries where investors' property rights are better legally protected. A U.S. based study by Durnev et al. (2003) show that lower R^2 statistic, or higher firm-specific variation, indicates prices closer to fundamentals, which results in more informational efficient stock prices and more efficient capital allocation. Durnev et al. (2004) explore capital budgeting decisions and find that lower market synchronicity leads to more efficient corporate investments.

Peress (2010) provides evidence for a positive relationship between industry structure and price informativeness. Industry mispricing caused by investor misvaluation is expected to vary across industries depending how susceptible industries are to investor speculations.

Less industry specific information suggests that investors rely more heavily on the overall market risk when trying to valuate certain stocks. Therefore, market risk has greater weight in pricing these industries. Since sentiment is considered to be a systematic risk, it should have a more pronounced effect on industries that move with greater synchronicity with the market. This results in our forth hypothesis:

H4: The effect of investor sentiment on cost of equity is more pronounced for industries with a poorer information environment, measured by higher market synchronicity.

Given all theoretical arguments and supportive empirical findings, we believe that product and capital markets are interrelated. Thus, studying industry based valuation in the investor sentiment context, taking into account industry concentration, product market uniqueness and stock market synchronicity with the market, would make a valuable contribution to the existing literature of behavioural finance. Moreover, this paper aims to provide empirical evidence on the effect of sentiment on expected cost of equity capital measured using forward-looking valuation models.

CHAPTER 4
DATA AND VARIABLES

4.1. Investor Sentiment

Our main sentiment proxy is the Michigan Consumer Confidence Index provided by Michigan Consumer Research Center, SENTIMENT (S).[3] Our choice of sentiment proxy is mainly motivated by Lemmon and Portniaguina (2006) and Qui and Welch (2006) who show that consumer confidence has an effect on asset valuation. As argued by Qui and Welch (2006), Michigan Consumer Confidence Index focuses more on financial conditions compared to other consumer surveys whose focus is mainly on macroeconomic factors. Thus, Michigan Consumer Confidence Index is a better measure of economy-wide sentiment and suits the purpose of our study. We obtain annual data for the Michigan Consumer Confidence Index from Federal Reserve Economic Data.[4]

4.2. Industry Cost of Equity Estimates

In order to compute the cost of equity estimates, financial data is obtained from Research Insight/Compustat database and analysts' earnings forecasts and pricing information from Thompson Institutional Brokers Earnings Services (I/B/E/S). All firms contained in the Compustat files for the period between 1990 and 2006 are downloaded and then matched to the companies covered in I/B/E/S summary files. All cost of equity estimates are computed as of the month of June of each firm year.[5] All firms are required to have:

- a positive mean earnings forecast for the first 2 years;
- a reported long-term growth rate: either a 5-year mean growth rate or a 3-year earnings forecast;
- at least two analysts providing earnings forecasts for years 1 and 2;

[3] For robustness, we also use Baker and Wurgler's (2006) composite sentiment index, which relies on measures derived from financial markets. It is based on the first principal component of six popular sentiment proxies: value-weighted dividend premium (Baker and Wurgler, 2004), IPO volume (Ibbotson, Sindelar and Ritter, 1994), closed-end fund discount (Neal and Wheatley, 1998), equity share in new issues (Baker and Wurgler, 2000), and NYSE turnover (NYSE Factbook). These six proxies are standardized and each of them has been also orthogonalized with respect to a set of macroeconomic conditions. The data is available from Jeffrey Wurgler's official website, http://pages.stern.nyu.edu/~jwurgler/.

[4] http://research.stlouisfed.org/fred2/series/UMCSENT/ . The data is not seasonally adjusted and the units of the downloaded series is "Natural Log of Index 1st Quarter 1966=100."

[5] The cost of equity estimates are obtained from Mamun and Mishra (2010).

- a price for the corresponding statistics record period in the I/B/E/S price history file.

Previous research proposes several models for estimating the implied cost of capital. All of them are based on the discount cash flow valuation theory. However, as they vary in their implementation, the derived estimates have different properties. In order to avoid spurious results associated with the use of only one model, we adopt the approach of Dhaliwal et al. (2006) and Boubakri et al. (2010) and compute the average cost of equity based on the four models: Gebhardt et al. (2001), Claus and Thomas (2001), Ohlson and Juettner-Nauroth (2005), and Easton (2004).[6] We subtract the 3-month US Treasury bond yield from the estimated cost of equity, which gives us the implied equity risk premium that we use as our dependent variable (r_{avg}).

Then, we estimate industry level risk premium proxies using industry-year average of the cost of equity premiums for all firms within a certain industry based on Fama and French 48 Industry Classification. Our choice of industry level analysis further mitigates the concern of spurious results and aims to provide a better proxy of industry average cost of equity. We require that firms have all four estimates of cost of equity in order to be included in our sample. This results in 679 Fama-French industry-year observations for non-financial industries.

4.3. Information Availability

In order to obtain a market synchronicity proxy as a measure for information availability, we use the R^2 statistic from market model regressions. Previous literature (Roll, 1988; Durnev et al., 2003; Durnev et al., 2004) obtain firm-specific variation by regressing firms' total returns on market and industry returns. For our industry level analysis, we start by calculating the R^2 statistic by regressing firm excess returns on the excess market returns and then averaging the R^2 statistics by industry following Fama and French's 48 industry classification.

The R^2 estimates are based on monthly stock returns from the Center for Research in Security Prices (CRSP) for the period between 1987 and 2006. The market portfolio proxy is the CRSP value-weighted market index. We require that the excess returns over the risk free rate for both firm and market level have minimum of 36 valid return observations in a window of 60 months preceding the month of December for each year. Then, we run the following regression

[6] For a detailed description of the four models used for estimating cost of equity refer to Appendix C.

each year for firm *i* over the past 60 months:

$$r_{i,j,t} = R_{i,j,t} - R_{f,j,t} = \alpha_{i,t} + \beta_{i,t}(R_{m,j,t} - R_{f,j,t}) + \varepsilon_{i,j,t} , \tag{4.1}$$

where

$r_{i,j,t}$ is firm *i's* excess return in past month *j* for year *t*,

$R_{i,j,t}$ is firm *i's* total return in past month *j* for year *t*,

$R_{f,j,t}$ is the risk-free rate (3-month US Treasury Bill) in past month *j* for year *t*,

$R_{m,j,t}$ is the value-weighted market portfolio return in past month *j* for year *t*,

$\beta_{i,t}$ is firm *i's* market beta for year *t*, and

$\varepsilon_{i,j,t}$ is the residual from the market model regression for firm *i* in past month *j* for year *t*.

Using the R^2 statistics from the regressions above, we calculate R_I^2-year averages across all firms within industry *I* of each Fama and French 48 industry classification for each year. In order to distinguish systematic variation and firm-specific variation, we follow Roll (1988) and use a standard variance decomposition, which let us express industry-average R^2 which by definition is $R^2 = \frac{SSE}{SSR+SSE}$, where SSE is the explained variation, and SSR is the unexplained variation. Equivalently:

$$R_I^2 = \frac{\sigma_{m,I}^2}{\sigma_{\varepsilon,I}^2 + \sigma_{m,I}^2}. \tag{4.2}$$

Consistent with the practice in the literature,[7] we define a R_I^2 based measure that we use as our dependent variable SYNCH:

[7] Roll (1988) uses (1 - R^2) as a proxy for information availability. However, Durnev et al. (2004), Durnev et al. (2003) circumvent the bounded nature of $R^2 \in [0,1]$ by using a logistic transformation:

$$\Psi = \ln\left(\frac{1 - R_I^2}{R_I^2}\right),$$

where $\Psi \in \Re$. For the purpose of our analysis we adopt a synchronicity measure in the form:

$$SYNCH = -\Psi = \ln\left(\frac{R_I^2}{1 - R_I^2}\right),$$

which increases with R_I^2.

$$SYNCH = \ln\left(\frac{R_I^2}{1-R_I^2}\right). \quad (4.3)$$

This transformation also has the characteristic that:

$$SYNCH = \ln(\sigma_{m,I}^2) - \ln(\sigma_{\varepsilon,I}^2). \quad (4.4)$$

Thus, a higher SYNCH indicates that the portion of explained variation is relatively greater than the portion of unexplained variation, implying a lower firm-specific return variation. On the other hand low SYNCH implies high firm-specific variation. As argued by the literature (Morck et al., 2000, Durnev et al., 2003), stocks with a high firm-specific return variation are relatively less sensitive to market risk factor, hence they are more likely to have a low SYNCH. Equivalently, SYNCH measures the lack of information availability as it is inversely related to the level of firm-specific information available in the market.

4.4. Industry Concentration

We measure industry concentration using the Herfindahl index, which is defined as:

$$Herfindahl_I = \sum s_{iI}^2. \quad (4.5)$$

Where s_{iI}^2 is the market share of firm *i* in industry *I*. We use net sales (Compustat item #12) scaled by total industry sales to calculate market share for all Compustat firms in each industry according to Fama and French 48 Industry classification in the period 1990 to 2006 (Masulis et al., 2007). The Herfindahl index provides information about the level of competition that exists within an industry, and also about the distribution of market share across the firms included in the index. Small values of the Herfindahl index imply that the industry is highly competitive and market shares are more evenly distributed across market participants, while large Herfindahl values mean greater market concentration in the hands of few firms. We define an industry as competitive if the Herfindahl index is in the bottom quartile of all 48 Fama and French industries following Masulis et al. (2007).

4.5. Product Uniqueness

Product uniqueness is defined as the industry's median ratio of selling expenses (Compustat item #189) scaled by sales (Compustat item #12). Wessels and Titman (1988) argue that firms that produce specialized products tend to spend more in promoting and selling their products. Therefore, selling expenses over sales should be positively related to uniqueness. Following Masulis et al. (2007) we define an industry as unique if it is in the top quartile of all Fama and French (1997) industries for each year.

4.6. Control Variables

When specifying our control variables we follow previous research that has nominated several variables as significant determinants of the cost of equity estimates (Gebhardt et al., 2001; Dhaliwal et al., 2006). We follow closely the cost of equity controls proposed by Dhaliwal et al., (2006) who control for risk by including Fama and French three risk factors suggested in their study on industry cost of capital: $bMKT, bSMB$ and $bHML$. We borrow the industry level averages of loadings for Fama and French (1993) risk factors from Mamun and Mishra (2010).[8]

We use bMKT – the industry average loading beta from regressing firms' excess returns on market excess returns - to control for the effect of systematic risk. The Capital Asset Pricing Model suggests a positive correlation between market beta and cost of equity. Botosan (1997) and Dhaliwal et al. (2006) find a significant, positive correlation between implied cost of capital and beta. Therefore, we expect a positive relationship between the cost of equity estimates and bMKT.

In our models we use the industry average of bSMB – the loading against the portfolio of small minus big firms - as a proxy for size, which is associated with information availability. Investment risk increases when information about the firm is difficult to obtain. Larger firms and firms with greater analyst coverage (as a proxy for information availability) are expected to have a lower cost of capital because easily available information lowers the information asymmetry between a firm and its investors (Gebhardt et al., 2001, Easley et al., 2002). Thus, we expect that cost of equity is positively related to out proxy for size and information availability – bSMB.

bHML is the loading against the difference between the returns to a portfolio of high book to market stocks and the returns to a portfolio of low book to market stocks. Since high book to market ratio suggests lower growth opportunities, lower accounting conservatism or higher perceived risk (Gode and Mohanram, 2003), literature predicts a positive relationship with cost of equity (Aggarwal et al., 2011). If these types of stocks are undervalued, they should earn

[8] The three risk factors $bMKT, bSMB$ and $bHML$ are estimated using a minimum of 24 observations of firm-level monthly excess returns over the past 60 month ending in December of the year when the cost of equity is estimated and regressing them on Fama and French's three factors.

an abnormally high implied risk premium until the mispricing is corrected (Fama and French, 1992). The positive association with book to market ratio has already been documented in the cost of equity literature (Dhaliwal et al., 2006; Hail and Leuz, 2006; Guedhami and Mishra, 2009) Thus, we would expect cost of equity to be positively related to bHML.

In theory, a firm's risk premium should be an increasing function of the amount of debt in its capital structure (Modigliani and Miller, 1958). Fama and French (1992) document a positive relationship between market leverage and ex post mean stock returns (average of historical returns). Empirical evidence about the positive relationship between leverage and cost of equity has been shown by Gode and Mohanram (2003) and Dhaliwal et al. (2006). Based on theory and empirical results, we expect that leverage has a positive effect on implied risk premium. We measure leverage as the ratio of total debt to total capital.

Earnings forecast variability is a source of risk for firm valuation. It also tends to capture fundamental cash flow risk (Gebhardt et al., 2001). We measure earnings forecast variability as the industry average of the standard deviation of one year ahead analysts' earnings forecasts scaled by the mean of one year ahead earnings forecasts (COEFVAR). This variable captures the disagreement among analysts regarding earnings forecasts and the way it is constructed makes it comparable across firms with different number of analysts following (Aggarwal et al., 2011). Thus, firms with high earnings forecast variability would be harder to value objectively because there is more information asymmetry between the firm and the investors. Therefore, these firms are riskier and are expected to have higher cost of equity (Gode and Mohanram, 2003).

La Porta (1996) shows that because of analysts' systematic optimism, high long-term growth firms earn lower subsequent returns. Thus, there should be a negative relation between forecasted long-term growth and subsequent implied risk premium. Gebhardt et al. (2001) also hypothesize a negative association between growth and risk premium. However, it should be noted that analysts may be optimistic about future earnings, but as long as they use the correct discount rate, their optimism will lead to an inflated price rather than overstated risk premium. Gode and Mohanram (2003), Dhaliwal et al. (2006) and Guedhami and Mishra (2009) predict a positive effect of growth on cost of equity estimates. The argument is that high-growth firms are generally perceived as risky, hence the positive relationship between growth and risk premium. We measure *Growth* as the mean long-term earnings growth rate from I/B/E/S and expect a positive relationship with the cost of equity.

4.7. Descriptive Statistics

Table 1, Panel A presents descriptive statistics for the cost of equity capital estimates using the four models. We use industry-year averages across the Fama and French 48 Industry Classification between 1990 and 2006 that results in 679 total observations. Consistent with the findings in recent research (Hail and Leuz, 2006; Dhaliwal et al., 2006) the Ohlson and Juettner-Nauroth model (k_{OJ}) provides on average the highest estimate for the cost of equity 13.46% as opposed to the model of Gebhardt et al. (2001) (k_{GLS}) which gives the lowest estimate, 8.53%. k_{OJ} is also the estimate with highest standard deviation: 2.33%.

The mean industry average annual cost of equity based on all four models (k_{avg}) over the sample period is 11.3% with standard deviation of 1.85%. For the purpose of our analysis we use the implied risk premium (r_{avg}), which equals the industry year-average cost of equity estimate (k_{avg}) minus the risk free rate (3-month US Treasury Bill) measured in June of each year (Hail and Leuz, 2006; Dhaliwal et al., 2006; Mamun and Mishra, 2010). The average implied risk premium in our sample is 7.36% with a standard deviation of 2.08%.

Panel B of Table 1 provides pair-wise correlations between the cost of equity estimates. The correlation between the four measures ranges from 35.6% to 98.79%. This is quite high correlation, as pointed out by Guay, Kothari and Shu (2003), is due to the fact that all four models rely on the same inputs such as stock price and analysts' earnings forecasts and use the same technique of discounted cash flow valuation models. The average of the four models k_{avg} has the highest correlation with Easton's estimate (k_{ES}) and the lowest withk_{GLS}.

Tables 2 and 3 provide descriptive statistics and pair-wise correlations of the main tests and control variables. The industry sample breakdown is summarized in Table 4. The R^2 from the market model regressions for each industry are, as expected, generally pretty low ranging from 0.06 to 0.22. SYNCH is therefore negative and it varies in the same direction as R^2 estimated from the market model regressions from each industry, meaning low R^2 industries also have low SYNCH and vice versa. The industry with the best information environment (measured by the lowest SYNCH) is the Precious Metals industry, whereas the industry with the worst information availability to investors is Communication.

The table also identifies the high-tech, unique, and competitive industries in our sample. The values for unique and competitive industries range between 0 and 1 because an industry is classified as unique/competitive based on calculations each year and the table presents averages over the whole sample.

CHAPTER 5
EMPIRICAL RESULTS

In this section we test our hypotheses by estimating several specifications of the following basic model:

$$r_{avg} = \alpha + \beta \times Sentiment + \gamma \times Controls + \varepsilon. \tag{5.1}$$

Table 5 reports our main results. In each model we use industry average implied cost of equity premium r_{avg} as our dependent variable. All models include controls that have been suggested by the literature as significant determinants of a firm's cost of equity – industry level averages for Fama and French three risk factors: bMKT, bSMB, bHML; leverage, growth and earnings forecast variability. Our test variable in Model 1 through Model 11 is SENTIMENT – natural logarithm of the Michigan Consumer Confidence Index.

In Model 1 we see that the coefficient on SENTIMENT is negative and statistically significant at 1% level, suggesting that investor optimism is associated with a lower industry average risk premium. This significant relationship remains when we include the control variables previously discussed (Model 2) and supports the expected negative relationship between market-wide investor sentiment and industry cost of equity proposed in *Hypothesis 1*. This finding is in line with previous research that finds sentiment affecting expected returns (Brown and Cliff, 2004; Wurgler and Zharavskaya, 2002; Baker and Wurgler, 2005, 2006). More specifically, our results suggest that overly optimistic/pessimistic attitude in the market has an impact not only on expected cash flows, but investors also adjust the discount rate they use for valuating certain stocks in correspondence with their sentiment. As a result, we observe that overvaluation due to market's general positive attitude leads to lower risk premiums, whereas prevailing pessimism among investors results in undervaluation or subsequent higher risk premiums.

As far as the controls, only bHML, leverage and growth appear to be significant and they show with the expected positive sign. Since we perceive sentiment as a market wide risk, one possible concern is that market risk, measured by beta (bMKT), can absorb the sentiment effect. However in our case, the bMKT coefficient is not statistically different from zero, whereas sentiment is highly significant. This significance might be due to a relationship between sentiment and the general systematic risk in the market. However, the correlation between sentiment (SENTIMENT) and market risk (bMKT) is -0.072 (not statistically significant), so they appear to measure different effects, and we needn't be concerned with multi-collinearity issues between them.

In *Hypothesis 2* we predict that competitive industries are more susceptible to investor optimism/pessimism, hence, the effect of sentiment on cost of equity should be more pronounced for industries with lower concentration. In order to test these predictions, we regress cost of equity on the interaction between SENTIMENT and a dummy variable identifying competitive industries (COMPETITIVE). Ideally, the model should include both the interaction term as well as the dummy variable for competitive industries. However, due to the high correlation between the two, we have to test their effect on sentiment separately.

In Model 3 the strong negative relationship between cost of equity and sentiment remains. However, the coefficient for COMPETITIVE is not statistically different from zero. This does not support previous empirical findings about the negative relationship between market concentration and capital cost. Hou and Robinson (2006) show that competitive industries are riskier and have higher expected returns even after controlling for size, book to market ratio and momentum. However, the main goal of our paper is to test the effect of sentiment, therefore we are more interested in the interaction term between sentiment and industry competition (S×COMPETITIVE). If the effect of sentiment on industry risk premium is stronger for competitive industries, we expect the coefficient on the interaction term to be negative. In other words, as firms in competitive industries are found to be more volatile, less liquid and associated with greater information uncertainty (Gaspar and Massa, 2006; Peress, 2010), they are expected to be affected by sentiment to a greater extent since these are the types of firms subject to speculation and lack of objective valuation. In Model 4 we find that the coefficient for the interaction term S×COMPETITIVE is not statistically significant suggesting that sentiment has no marginal effect for competitive industries and we reject *Hypothesis 2*.

Next, we examine the effect of sentiment on product uniqueness. Firms with highly specialized products can be thought of as intrinsically speculative stocks. Since they don't have direct substitutes, this makes their valuation highly subjective and uncertain. In the behavioural framework, this means that these would be the type of stocks most subject to investor overreactions. Another theoretical argument of our *Hypothesis 3* is provided by Aspara and Tikkanen (2008) who argue that since individual investors (who are identified with noise traders) are also consumers in the product markets, attitudes toward certain products are shifted over to the firm producer, which in turn affects the tendency of these individuals to hold/buy stocks of the same companies and individuals' expectations about these firms' performance.

From our sample breakdown by industry (Table 4), we notice that many unique industries actually belong to the consumer goods and services sector, for example Candy and Soda, Beer and Liquor, Tobacco Products, Recreation, Consumer goods, Apparel and Retail.[9] The other group that can be identified among the unique industries are the high tech industries, (which we also examine separately).

Therefore, as *Hypothesis 3* states, we expect the marginal effect of investor sentiment to be higher for unique industries. Similarly to our tests for the competitive industries, we examine the effect of unique industries on cost of equity by including only a dummy identifying unique industries (UNIQUE), as well as focus on the marginal effect of sentiment on this type of industries since these two variables are highly correlated. Model 6 includes our sentiment proxy SENTIMENT, the interaction term S×UNIQUE and controls. The coefficient of the interaction term is statistically significant at 5% and indicates that the cost of equity associated with sentiment increases for industries classified as unique, which supports *Hypothesis 3.*

However, when we test the general effect of unique industries on cost of equity in Model 5, we find that the coefficient of UNIQUE is negative and statistically significant at 5%. This suggests that unique industries exhibit a lower cost of equity, which contradicts our expectations. The intuitive interpretation is that as unique industries are hard to value objectively, investors might perceive them as riskier and might require higher returns on their investment. Contrary to this logic, we find a significant negative relationship between unique industries and the corresponding industry cost of equity.

One possible explanation for this finding might be that certain industries that we classify as unique might actually operate in a monopolistic/oligopolistic market, which means that they have higher market power. In this case, unique industries might be thought of as the opposite of competitive industries. In this case our results support the literature as Hou and Robinson (2006) find that investors require a lower rate of return for high concentration industries because they are less exposed to distress risk. Nevertheless, this argument fails to explain why unique industries are subject to sentiment to a greater extent since market power is associated with less volatility and more information about the firm/industry (Perres, 2010).

[9] It might be surprising that consumer goods would be considered "unique," but this may be related to brand loyalty.

Another sector that deserves special attention is the high-tech industries. Our classification of high-tech industries is based on Grullon et al. (2010). In our sample high-tech industries are: Electrical Equipment, Communication, Computers, Electronic Equipment and Measuring and Control Equipment. More than half of the high-tech industries are also classified as unique, which as discussed above, are expected to be more susceptible to sentiment and our results supported this. Moreover, high-tech industries consist of growth firms, investor sentiment literature considers as prone to investor misevaluation. Lastly, the history of financial markets has a clear evidence of investor speculation over the high-tech sector. In the late 1990s technology stocks were subject to a lot of speculation as at that time technology companies were perceived to have great growth opportunities, whereas their stock valuation was not straightforward. Cooper et al. (2001) find evidence that companies that included "dot.com" or "dot.net" to their names during the internet bubble experienced increase in their stock price as great as 74% even though no other feature of the business was altered. As opposed to this trend, in the 2000s during the bear market, companies that removed those abbreviations from their names realized gains. This is a clear example of how prevailing emotions impact the stock market.

Based on this evidence, we expect to find that firms operating in the high technology industries are perceived as riskier by investors, and subject to noise traders' overreaction. Overall, we document no additional perceived risk associated with high tech industries and no marginal effect of sentiment on these industries.

We previously showed that unique industries consist mainly of consumer goods and services, as well as high-tech industries. Since, we find no evidence that sentiment affects high-tech industries to a greater extent, the more pronounced effect of investor overreaction on unique industries could be driven entirely by consumers and their perceptions formed in the product markets.

As far as the controls in our models, the coefficient of the systematic market risk proxy *b*MKT is positive but it is not statistically different from zero. A weak or no relationship between cost of equity and market beta is documented by other studies such as Gebhardt et al. (2001). The second Fama and French risk factor is bHML, which similarly to the book to market equity ratio, reflects growth opportunities or perceived risk. The coefficient of bHML is positive and statistically significant at 5%, which is in line with previous findings in the implied cost of equity literature. Gode and Mohanram (2003) and Hail and Luiz (2006) find a positive effect of the raw book to market equity ratio on firm's cost of equity. Similarly, the positive relation is observed by Dhaliwal et al. (2006) using the Fama and French risk loading bHML. The third risk factor bSMB is our proxy for firm size, which is associated with information availability; hence we expect a positive effect of size on the equity risk premium. The coefficient does load with a positive sign; however, it is not statistically significant in either of the models. LEVERAGE and GROW appear statistically significant with the expected positive sign through Model 1 to Model 8 in Table 5. COEFVAR has statistically significant effect on the risk premium in all models except for Model 5 and Model 6. However, the coefficient is statistically significant only at 10%.

Since speculation and stock misevaluation has a lot to do with lack of information about the firm/industry in question, we want to explore how information availability influences sentiment effects. Following recent literature that relates idiosyncratic variation to the level of information availability (Roll, 1988, Morck et al., 2000, Durnev et al., 2003), we use SYNCH as a measure for industry information quality.

Hypothesis 4 proposes that the effect of investor sentiment on cost of equity is more pronounced for industries with higher information asymmetry. In order to test this, we use interaction terms between sentiment and our synchronicity measure SYNCH. Our main results are presented in Table 5B.

Higher SYNCH implies less industry specific information (Durnev et al., 2004). Less industry specific information means that when investors valuate these industries, they rely more on the market risk as a whole because of lack of specific information about the industries in particular. As a result, market risk has greater weight in pricing these industries. Since sentiment is considered to be a systematic risk, then it should have greater effect on industries that move with greater synchronicity with the market.

In order to test this, we focus on the marginal effect of sentiment on risk premium in industries with different levels of information asymmetry (Table 5B).[10]

First we separate our sample into two: industries above the median SYNCH for the whole sample, and industries below the median. This way, the industries with above the median SYNCH can be thought of industries with low information availability, whereas below the median SYNCH industries are thought to have more industry-specific information available to in-

[10] Mishra and Shrestha (2010) examine the relationship between information availability measured in a manner that is inverse of our measure of synchronicity and cost of equity estimates derived from ex ante valuation models and find that cost of equity is a negative function of information availability.

vestors We would expect industries with lower SYNCH and higher industry specific variation to be less affected by sentiment. On the other hand, since high SYNCH industries are associated with worse information environment; they will be more susceptible to mispricing caused by the prevailing investor sentiment in the market.

In Model 9 (Table 5B) we use an interaction term between SENTIMENT and a dummy identifying industries with low SYNCH (LOW). The general effect of sentiment on industry risk premium is -0.0484 and it is statistically significant at 1%. The coefficient of S×LAW is also negative and statistically significant. This evidence suggests that the effect of sentiment is stronger for industries with lower synchronicity, which contradicts our theoretical argument that if there is more industry-specific information in the market, proxied by low SYNCH, the valuation of the firms operating in these industries will be more straightforward, less subject to speculative mispricing and, therefore, these industries will be less affected by the overall market sentiment. In other words, if SYNCH indeed measures information asymmetry, our results suggest that industries with higher information asymmetry experience less mispricing due to investor optimism/pessimism.

In order to provide a more thorough analysis about the differences in the effect of sentiment across different levels of information quality, we sort our sample on market synchronicity (SYNCH) and divide it into quintiles. Models 10 – 14 respectively include an interaction term between a dummy for each one of the quintiles of SYNCH and SENTIMENT. We find supportive evidence of what we observed in Model 9 – the misvaluation due to investors' overreaction is more pronounced for industries with low market synchronicity. The marginal effect of sentiment associated with the bottom quintile of SYNCH is -0.0013 and statistically significant at 1% (Model 10). We find no evidence that sentiment has any marginal effect for industries with high SYNCH (quintiles 4 and 5). However, we do find that sentiment has more pronounced effect on cost of equity for industries with medium synchronicity (Model 12).

Since we hypothesize that the impact of sentiment on cost of equity should be different depending on whether industries are identified as competitive, unique and having good information environment, our models should ideally include SENTIMENT, an intercept dummy (identifying the respective industry feature) and a slope dummy (the interaction between sentiment and a dummy for competitive, unique and high market synchronicity industries). However, the industry features dummies and the corresponding interaction terms are highly correlated. For example, the correlation between LOW and S×LOW is 99.95%. We should note that this high correlation is expected given the low variation of our sentiment proxy. On one hand, omitting the dummy variable LOW we might be forcing the interaction term to explain more than it actually does. On the other hand, including both terms would cause multicollinearity issues in the regression models. That is the reason why we test the slope and the intercept dummies separately, and this is one of the limitations of our study.

In addition, we should note that our results are heavily affected by the interpretation of SYNCH as a proxy for the information environment. Roll (1988) suggests that low R^2 from the market model is potentially due to firm's returns capturing unique firm-specific information or reflecting greater idiosyncratic noise. Morck et al. (2000), Durnev et al. (2003) and a number of other studies reject the notion that idiosyncratic volatility is caused by noise traders and attribute it to trading activities of informed arbitrageurs.

Interpreting low SYNCH as a measure of good information availability is plausible in a market with no frictions and rational investors. Then price equals fundamental values and stock volatility would reflect new information incorporated in the price. However, in the framework of behavioural finance, agents are irrational and subject to sentiment. Therefore behavioural biases, bubbles, momentum, herding and other non-fundamental factors could affect stock return volatility (Barberis et al., 2005). As a result, our synchronicity measure might capture other market factors along with the firm-specific information.

For example, volatility in the market might be due to institutional herding, which does not necessarily lead to new information in the market. Neither is it associated with prevailing noise trader sentiment. Lee (1992) shows that institutional investors tend to trade in larger volumes than individual investors, which may induce greater volatility. It is also argued that institutional investors are more susceptible to herding behaviour because of the interrelated nature of the institutional investor community, the competition for better performance among them, and lastly, the asymmetry of incentives. In other words, the losses caused by underperformance are greater than the gains from overperformance. Such herding may aggravate price movements and increase volatility (Sias, 1996).

An opposing view to that proposed by Morck et al. (2000) is that market synchronicity is increasing in the quality of the information environment. Kelly (2007, p.31) finds empirical evidence that a low market synchronicity environment is actually characterized by "*lower institu-*

tional holdings, lower breadth of institutional ownership, lower analyst coverage, higher transactions costs, lower liquidity, greater private information risk, fewer information events, and a lower flow of informed trades." Consistent with this finding, Evans (2010) finds that firms with lower synchronicity are predominantly traded by individual investors. Her study shows that higher levels of trading by retail investors result in more firm-specific return variation and this relationship is more pronounced for smaller firms. Evans (2010) also finds that this negative relationship between retail trading volume and synchronicity remains significant for firms in industries that are generally more sensitive to the overall market conditions (such as finance and construction).

Since retail investors are identified with noise traders, sentiment should affect mainly stocks traded/held by these individual investors. Based on the findings of Evans (2010), these would be the firms with lower SYNCH. The sign of the interaction terms in Models 9 and 10 (Table 5) support this notion. We found a stronger marginal effect of sentiment for low SYNCH industries and no marginal effect of sentiment for industries with higher SYNCH.

Similarly to the models in Table 5A, bHML, leverage and growth seem to be consistently significant and have positive signs, as expected, in all three models. However, earnings variability (COEFVAR) is significant for all models with significance of 10%.

One could argue that adding a measure for information availability while keeping a control for information availability (bSMB) is redundant. However, even though size is often considered as a proxy for information asymmetry between a company and investors, it captures a number of other risk characteristics (e.g. firm's earnings stability, liquidity, associated risk) and it is important to be considered when examining cost of equity. Market synchronicity, on the other hand, captures idiosyncratic volatility that is nominated by the literature as a proxy of firm specific information being incorporated in the price. Moreover, based on the descriptive statistics, the correlation of size and market synchronicity is 10% so we are not concerned with collinearity issues.

CHAPTER 6
ROBUSTNESS TESTS

6.1.One Way Industry Fixed Effects

Since we study a panel of industry average cost of equity capital from 1990 to 2006, using an Ordinary Least Squares (OLS) regression might provide a biased estimator. The common solution is a fixed effects model. Even though this is the common practice in studies using multi-dimensional data, in our case our main test variable – sentiment – varies only across years but not across industries. Therefore including year fixed effects is not applicable. A one-way industry fixed effects is reasonable, although one concern is that much of the cross-industry variation would be eliminated and this is exactly what our focus is on - the effect of sentiment across industries. However, in order to be thorough and test whether our results are robust we use industry fixed effects. So, our model has the following specification:

$$r_{avg} = \alpha + \beta \times Sentiment + \gamma \times Controls + \delta \times Industry\ Fixed\ effects + \varepsilon. \tag{6.1}$$

These results are presented in Tables 6A and 6B. We replicate the main models from Tables 5A and 5B. In sum, the strong negative relationship between sentiment and implied risk premium remains throughout all models (coefficient of SENTIMENT is significant at 1%). In Models 5 and 6 of Table 6A we see that the effect of unique industries has disappeared. Competitive industries dummy as well as the interaction term with sentiment have no explanatory power, similar to our results using OLS estimates.

The marginal effect of sentiment for high-tech industries appears to be statistically significant at 5% and carrying the expected negative sign. As we hypothesized high-tech industries are easier to speculate with because of their high growth opportunities and the specialized nature of their product. However, this result is not significant when using OLS without industry fixed effects.

Hypothesis 4 is tested in models 8 to 10. While the coefficients of our synchronicity proxy and the corresponding interaction terms with sentiment were highly significant in the OLS regressions (1%), here they are not statistically different from zero.

6.2. Raw Cost of Equity as a Dependent Variable

Our choice of implied risk premium as a dependent variable is in line with recent studies incorporating ex ante valuation models (Dhaliwal et al., 2006, Hail and Luiz, 2006, El Ghoul et al., 2011). However, we conduct our tests using the cost of equity estimates (without subtracting the risk-free rate) instead in order to see whether the results are robust. Table 7 shows that the coefficient for sentiment is still negative and statistically significant. All four hypotheses previously tested are supported by these results as well. The major difference is in the significance of the control variables. Here, as opposed to the models using risk premium as dependent variable, the proxy for systematic risk (bMKT) is significant but appears with negative sign, suggesting that higher market risk lowers industry average cost of equity. bHML is no longer significant. On the other hand, bSMB, which previously showed to have no effect of risk premium, now has highly statistically significant coefficient estimate with the predicted positive sign. Leverage and growth, similarly to that in our main models, have significant positive effect on cost of equity.

6.3.Lagged Sentiment

As mispricing is hard to identify directly, the general approach is to look for systematic patters of correction of mispricing (Baker and Wurgler, 2006). For example, current optimism among investors results in overvaluation, so future returns would be lower as the market price reverts to its intrinsic value. This ex post evidence of mispricing is over different time horizons, ranging from 1 month to 3 years (Brown and Cliff, 2005, Schmeling, 2009). Since we deal with annual data, we use same period sentiment and cost of equity estimates for our main tests as 12 months is usually considered a long enough period for correction of mispricing to take place. However, we also test whether lagged period sentiment still has significant effect over expected returns. Table 8 presents the empirical results of regressing equity risk premium in year t on sentiment in t - 1 with controls.

The negative relationship between sentiment and cost of equity remains significant in all model specifications. Sentiment does not have a marginal effect on cost of equity capital for competitive industries similar to our main findings, whereas lagged sentiment is more pronounced for industries with unique products. The interaction term between lagged sentiment and our information availability proxy – SYNCH, is still positive and significant but only at 10%. If we test the effect of sentiment on low/high synchronicity industries separately, however, the significance disappears. The coefficient associated with the effect of sentiment in high-tech industries is with the expected negative sign but it is not statistically different from zero.

6.4. Sentiment Measured in June

Cost of equity estimates are measured as of June in each year, while the sentiment measure is an average over all 12 months for the respective year. So the time alignment of our variables might cause some issues. For example, the prevailing sentiment at the time analysts make their forecast could be more relevant than the one that represents the general attitudes over the year. In order to test whether our results are robust, we repeat our analysis this time using the natural logarithm of the Michigan Consumer Sentiment Index in June for each year in our sample. The results are presented in Table 9. The coefficients of sentiment are a little larger in magnitude but still have a negative sign and are highly significant. The significance and signs of the rest of the test variables are comparable to our main test in Table 5. The only difference is regarding *Hypothesis 4* since the interaction terms between sentiment and industry synchronicity are not significant.

6.5. Alternative Sentiment Proxy

Since our results might be affected by our choice of the Michigan Consumer Confidence Index as an investor sentiment proxy, we adopt an alternative sentiment measure based on sentiment theory and relying on financial market data. We take Baker and Wurgler's (2006) composite index consisting of six different proxies proposed by different studies and shown to be associated with asset prices: value-weighted dividend premium (Baker and Wurgler, 2004), IPO volume (Ibbotson, Sindelar and Ritter, 1994), closed-end fund discount (Neal and Wheatley, 1998), equity share in new issues (Baker and Wurgler, 2000), and NYSE turnover (NYSE Factbook). Most of them are based on the premise that sentiment is spread in the market through the trading activities of retail investors.

In Table 10 we have replicated our main models, this time using Baker and Wurgler's index (SENT) as a sentiment proxy. We find again that the sentiment coefficients are negative and statistically significant. The only model where sentiment has no explanatory power is Model 8 that includes also an interaction term between sentiment and synchronicity. We do find a significant negative relationship for unique industries in Model 4, but no marginal effect of sentiment associated with this type of industries (Model 5).

The interaction terms between the composite index SENT and the overall information environment SYNCH, and the dummies for low and high SYNH industries respectively are not statistically different from zero. The regressions testing the effect of high-tech industries show similar results as our main tests – expected negative sign but no significance. The significant negative effect of sentiment (SENT) on equity risk premium is robust to adding industry fixed effects to the models.

6.6.Using the Four Cost of Equity Estimates Individually

We also run the main regressions using the four cost of equity estimates (Claus and Thomas, 2001; Ohlson and Juettner-Nauroth, 2005; Gebhardt et al, 2001; and Easton, 2004) separately as dependant variables. Results are presented in Tables 11 - 14. The negative relationship between SENTIMENT and cost of equity holds for all models except for the estimates based on Gebhardt et al. (2001). Table 14 shows that when we use k_{GLS} , the coefficient of SENTIMENT is actually positive but it is not statistically significant. Similarly, the coefficients of the interaction terms used to test the rest of the hypotheses appear to be statistically insignificant. The only exception is regarding Hypothesis 4 as the coefficient of S×SYNCH is negative and significant just as in our main results.

When we use the Ohlson and Juettner-Nauroth (2005) and Easton (2004) estimates we find significant marginal effect of sentiment in competitive industries. However, as opposed to our expectations, the effect of investors' overreaction seem to be less pronounced in this type of industries.

We find robust results about Hypotheses 3 and 4 across the models. However, when we use the cost of equity estimate derived from Claus and Thomas (2001) model, we don't find supporting evidence that the effect of sentiment on cost of equity varies across industries with different information availability.

CHAPTER 7
CONCLUSION

The existing literature suggests that retail investor sentiment is an omitted risk factor in standard asset pricing models. However, there is no clear evidence yet whether the effect of sentiment derives from expected cash flows or discount rates. Therefore, our research aims to test the effect of noise traders on the cost of equity using forward-looking valuation models and to see whether these effects vary across industries.

We find a strong negative relationship between sentiment and industry average cost of equity robust to different model specifications and sentiment proxies. We find no significant marginal effect of sentiment in competitive industries. However, when examining industries with highly specialized products, we observe that on average these industries are affected to a greater extent by the prevailing sentiment in the market.

Furthermore, we try to relate the impact of sentiment with different information environments across the Fama-French 48 industries. We observe a stronger sentiment effect for industries with low market synchronicity suggesting that higher industry specific volatility is associated with more pronounced misvaluation triggered by excessive optimism/pessimism by the noise traders.

This study makes several contributions to the existing literature in the field of behavioural finance. First, the empirical tests rely on forward looking estimates of cost of equity, which supposedly perform better and deal with many of the flaws related to using average realized returns. Second, even though the effect of sentiment on asset mispricing has been broadly explored, we address this question through new perspective, offering evidence that certain features of the product markets in which firms operate influence the effect of investor sentiment on industry cost of equity. Lastly, we add to the literature exploring market synchronicity by testing the marginal effect of sentiment associated with it.

As in all empirical work, our study has a number of limitations, which should be noted. First, because of the nature of the cost of equity estimates we are limited in our choice of data frequency. We conduct our analysis using annual data and this way we cannot explore more closely when the effect of sentiment takes place in time and how persistent this mispricing is. Second, we lack a direct measure of both the dependent variable as well as the main test variable. We have adopted a survey proxy, which requires the assumption that the respondents (US households) are identified with the individual investors who introduce noise in the capital market.

When we incorporate sentiment into asset valuation, there are a number of channels through which market overreaction could impact the required rate of return: amount of risk, price of risk, risk aversion, loss aversion, cognitive and emotional biases and of course the interaction of all of the above. The scope of our study is limited to the aggregate level of sentiment in the market, perceived as an omitted systematic risk factor and its effect on industry-average cost of capital. A more intrinsic decomposition and analysis of all factors contributing to investor sentiment in the capital market we will leave to future research.

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Table 1

Descriptive Statistics for the Implied Cost of Capital Estimates

Panel A: Distributional statistics for the cost of capital estimates

				Percentile				
Variable	**N**	**Mean**	**Min**	**Q1**	**Q2**	**Q3**	**Max**	**StDev**
$\boldsymbol{k_{CT}}$	679	0.105539	0.054638	0.090539	0.104845	0.117455	0.363334	0.022234
$\boldsymbol{k_{GLS}}$	679	0.085307	0.02463	0.074184	0.083557	0.092995	0.245375	0.019544
$\boldsymbol{k_{OJ}}$	679	0.134625	0.069739	0.117155	0.131975	0.146874	0.255687	0.024672
$\boldsymbol{k_{ES}}$	679	0.126918	0.070469	0.110921	0.123089	0.138147	0.251191	0.023291
$\boldsymbol{k_{avg}}$	679	0.113097	0.067213	0.099389	0.111798	0.123389	0.203525	0.018463

Panel B: Pearson correlation coefficients between cost of capital estimates

Variable	$\boldsymbol{k_{avg}}$	$\boldsymbol{k_{OJ}}$	$\boldsymbol{k_{ES}}$	$\boldsymbol{k_{CT}}$	$\boldsymbol{k_{GLS}}$
$\boldsymbol{k_{avg}}$	1				
$\boldsymbol{k_{OJ}}$	0.9068	1			
$\boldsymbol{k_{ES}}$	0.9112	0.9879	1		
$\boldsymbol{k_{CT}}$	0.7852	0.5546	0.5373	1	
$\boldsymbol{k_{GLS}}$	0.6548	0.356	0.3932	0.4888	1

This table reports descriptive statistics for the cost of equity estimates based on four models: Claus and Thomas (k_{CT}), Gebhardt et al. (k_{GLS}), Ohlson and Juettner-Nauroth (k_{OJ}) and Easton (k_{ES}). k_{AVGS} is the mean of the four estimates. The full sample consists of 679 industry-year averages across Fama and French 48 Industries in the period between 1990 and 2006. All correlation coefficients are significant at 1% level.

Table 2

Descriptive Statistics for Test and Control Variables

Variable	N	Mean	Min	Percentile Q1	Q2	Q3	Max	Stdev
SENTIMENT	679	4.52	4.30	4.50	4.50	4.60	4.70	0.11
$SENT_{BW}$	679	0.07	-1.00	-0.18	-0.02	0.15	1.92	0.64
LEVERAGE	679	0.38	0.07	0.30	0.38	0.46	0.94	0.13
COEFVAR	679	0.13	0.00	0.05	0.07	0.14	3.34	0.21
GROW	679	16.39	3.75	13.18	15.56	19.37	44.58	5.11
bMKT	679	0.90	-63.30	0.79	1.01	1.20	3.55	2.52
bHML	679	0.17	-9.98	-0.14	0.25	0.50	7.09	0.87
bSMB	679	0.59	-18.46	0.29	0.60	0.91	6.37	0.97
R^2	679	0.15	0.03	0.10	0.14	0.18	0.37	0.06
SYNCH	679	-1.84	-3.51	-2.17	-1.86	-1.52	-0.46	0.48
LOW	679	0.50	0	0	1	1	1	0.50
HIGH	679	0.50	0	0	0	1	1	0.50
HIGH_TECH	679	0.12	0	0	0	0	1	0.33
S x HIGH_TECH	679	0.56	0	0	0	0	4.70	1.49
UNIQUE	679	0.29	0	0	0	1	1	0.45
COMPETITIVE	679	0.25	0	0	0	0	1	0.43
S *x* UNIQUE	679	1.30	0	0	0	4.40	4.70	2.05
S *x* COMPETITIVE	679	1.11	0	0	0	0	4.70	1.95
S *x* LOW	679	2.28	0	0	4.30	4.50	4.70	2.28
S *x* HIGH	679	2.24	0	0	0	4.50	4.70	2.25
S *x* SYNCH	679	-8.33	-15.83	-9.84	-8.38	-6.73	-2.04	2.22

This table reports the descriptive statistics for the main test variables as well as controls. These are annual observations in the period between 1990 and 2006. SENTIMENT and $SENT_{BW}$ are our sentiment measures proxied by the Michigan Consumer Confidence Index and Baker and Wurgler's composite index, respectively. bMKT, bHML and bSML are Fama and French risk factors. Together with leverage (LEVERAGE), earnings variability (COEFVAR) and long-term growth (GROW) they represent our control variables. R^2 refers to the R-squared statistics from the market models run for each industry based on the Fama and French 48 industry classification. SYNCH stands for industry synchronicity measure. LOW and HIGH are dummies for below and above the median industry SYNCH respectively. UNIQUE is a dummy variable for unique industries, whereas COMPETITIVE refers to competitive industries dummy. HIGH_TECH is a dummy identifying high-tech industries. S x HIGH_TECH, S x UNIQUE, S x COMPETITIVE, S x LOW, S x HIGH and S x SYNCH represent interaction terms between the Michigan Consumer Sentiment Index and the respective industry characteristic. For a detailed description of the variables refer to Appendix A.

Table 3

Correlation Table

	LEVERAGE	*COEFVAR*	*GROW*	*bMKT*	*bHML*	*bSMB*	*SENTIMENT*	*SENT*	*UNIQUE*	*COMPETITIVE*	*SYNCH*	*LOW*	*HIGH*	*HIGH_TECH*	*S x HIGH_TECH*	*S x UNIQUE*	*S x COMPETITIVE*	*S xLOW*	*S xHIGH*	*S xSYNCH*
LEVERAGE	1.000																			
COEFVAR	-0.032	1.000																		
GROW	**-0.541**	0.005	1.000																	
bMKT	0.012	**-0.098**	0.063	1.000																
bHML	**0.233**	0.015	**-0.167**	0.044	1.000															
bSMB	**-0.120**	-0.022	**0.178**	**0.750**	**0.239**	1.000														
SENTIMENT	**0.098**	-0.032	**0.146**	-0.072	**0.196**	-0.018	1.000													
SENT	**0.086**	0.008	**0.153**	0.010	**0.138**	0.026	**0.585**	1.000												
UNIQUE	**-0.413**	**-0.078**	**0.247**	0.033	**-0.212**	0.009	0.005	0.007	1.000											
COMPETITIVE	-0.010	0.011	**-0.081**	0.050	0.027	0.016	-0.005	-0.003	**-0.130**	1.000										
SYNCH	-0.048	**-0.081**	0.005	**0.099**	**-0.114**	**0.101**	**-0.330**	**-0.339**	**0.119**	**0.229**	1.000									
LOW	0.073	0.039	0.027	**-0.076**	**0.104**	-0.062	**0.339**	**0.343**	**-0.103**	**-0.221**	**-0.790**	1.000								
HIGH	-0.073	-0.039	-0.027	**0.076**	**-0.104**	0.062	**-0.339**	**-0.343**	**0.103**	**0.221**	**0.790**	**-1.000**	1.000							
HIGH_TECH	**-0.328**	0.037	**0.258**	0.054	**-0.132**	**0.095**	-0.004	0.000	**0.274**	0.055	**0.198**	**-0.178**	**0.178**	1.000						
S *x HIGHTECH*	**-0.328**	0.037	**0.261**	0.054	**-0.131**	**0.096**	0.005	0.005	**0.274**	0.057	**0.197**	**-0.176**	**0.176**	**1.000**	1.000					
S x UNIQUE	**-0.412**	**-0.079**	**0.248**	0.032	**-0.208**	0.009	0.021	0.016	**1.000**	**-0.128**	**0.113**	**-0.097**	**0.097**	**0.274**	**0.274**	1.000				
S x COMPETITIVE	-0.010	0.010	**-0.078**	0.050	0.029	0.017	0.009	0.005	**-0.128**	**1.000**	**0.224**	**-0.217**	**0.217**	0.057	0.058	**-0.126**	1.000			
S x LOW	**0.077**	0.037	0.029	**-0.077**	**0.108**	-0.063	**0.358**	**0.356**	**-0.102**	**-0.220**	**-0.788**	**1.000**	**-1.000**	**-0.178**	**-0.176**	**-0.096**	**-0.216**	1.000		
S x HIGH	-0.073	-0.039	-0.023	0.075	**-0.100**	0.063	**-0.315**	**-0.333**	**0.104**	**0.224**	**0.785**	**-0.999**	**0.999**	**0.181**	**0.179**	**0.099**	**0.220**	**-0.999**	1.000	
S x SYNCH	-0.059	-0.075	-0.007	**0.104**	**-0.128**	**0.101**	**-0.410**	**-0.383**	**0.114**	**0.223**	**0.996**	**-0.796**	**0.796**	**0.195**	**0.193**	**0.108**	**0.216**	**-0.797**	**0.790**	1

This table presents Pearson correlation coefficients for the explanatory variables. The coefficients significant at the 5% level are in bold. Please refer to Appendix A for variables description.

Table 4.

Sample Breakdown by Industry

No	Industry	R^2	SYNCH	r_{avg}	High Tech	Unique	Competitive
1	Agriculture	0.12	-2.10	0.07	0	0	0
2	Food Products	0.11	-2.16	0.06	0	0	0
3	Candy & Soda	0.19	-1.53	0.06	0	1	0
4	Beer & Liquor	0.14	-1.96	0.05	0	1	0
5	Tobacco Products	0.13	-2.20	0.10	0	0.64	0
6	Recreation	0.13	-1.92	0.08	0	1	0
7	Entertainment	0.13	-1.92	0.07	0	0	0
8	Printing & Publishing	0.18	-1.59	0.06	0	1	0.35
9	Consumer Goods	0.16	-1.72	0.07	0	1	0
10	Apparel	0.13	-2.01	0.08	0	0.41	0.12
11	Healthcare	0.12	-2.09	0.07	0	0	0.06
12	Medical Equipment	0.11	-2.10	0.06	0	1	0.18
13	Pharmaceutical Products	0.14	-1.87	0.06	0	0.41	0.06
14	Chemicals	0.17	-1.60	0.07	0	0	0.35
15	Rubber & Plastic Products	0.13	-1.98	0.07	0	0	0.13
16	Textiles	0.12	-2.11	0.10	0	0	0.27
17	Construction materials	0.15	-1.75	0.08	0	0	0.59
18	Construction	0.14	-1.87	0.09	0	0	0.06
19	Steel Works	0.19	-1.50	0.10	0	0	1
20	Fabricated Products	0.12	-1.99	0.09	0	0	0
21	Machinery	0.16	-1.71	0.08	0	0	1
22	Electrical Equipment	0.15	-1.75	0.07	1	0	0
23	Automobiles & Trucks	0.18	-1.56	0.09	0	0	0
24	Aircraft	0.14	-1.92	0.07	0	0	0
25	Shipbuilding & Railroad Equipment	0.15	-1.76	0.08	0	0	0
26	Defence	0.14	-1.86	0.08	0	0	0
27	Precious Metals	0.06	-2.76	0.06	0	0	0
28	Non-Metallic & Ind Metal Mining	0.12	-2.00	0.07	0	0	0
29	Coal	0.17	-1.67	0.11	0	0	0
30	Petroleum & Natural gas	0.11	-2.13	0.08	0	0	0
31	Utilities	0.13	-2.06	0.06	0	0	1
32	Communication	0.22	-1.30	0.06	1	0.06	1
33	Personal Services	0.13	-1.96	0.06	0	0	0
34	Business Services	0.17	-1.60	0.06	0	1	0.41
35	Computers	0.16	-1.69	0.07	1	1	0
36	Electronic Equipment	0.19	-1.49	0.07	1	1	0.53
37	Measuring & Control Equipment	0.16	-1.72	0.07	1	1	0
38	Business Supplies	0.19	-1.51	0.09	1	0	0.59
39	Shipping Containers	0.18	-1.60	0.09	0	0	0

40	Transportation	0.16	-1.67	0.08	0	0	1
41	Wholesale	0.13	-1.92	0.07	0	0	0.06
42	Retail	0.15	-1.75	0.07	0	0.29	1
43	Restaurants, Hotels & Motels	0.14	-1.91	0.06	0	0	0.19

Table 5A

Sentiment, Implied Cost of Equity and Industry Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	r_{avg}	r_{avg}	r_{avg}	r_{avg}	r_{avg}	r_{avg}	r_{avg}	r_{avg}
Constant	0.2545***	0.2849***	0.2847***	0.2851***	0.2833***	0.2822***	0.2849***	0.2848***
	(8.688)	(9.529)	(9.518)	(9.540)	(9.577)	(9.541)	(9.524)	(9.521)
SENTIMENT (S)	-0.0400***	-0.0536***	-0.0538***	-0.0539***	-0.0526***	-0.0523***	-0.0536***	-0.0536***
	(-6.157)	(-7.769)	(-7.799)	(-7.815)	(-7.713)	(-7.666)	(-7.755)	(-7.749)
COMPETITIVE			0.0018					
			(1.065)					
S *x* COMPETITIVE				0.0004				
				(1.060)				
UNIQUE					-0.0037**			
					(-2.058)			
S *x* UNIQUE						-0.0008**		
						(-2.093)		
HIGH_TECH							-0.0003	
							(-0.157)	
S *x* HIGH_TECH								-0.0001
								(-0.223)
bMKT		0.0002	0.0001	0.0001	0.0002	0.0002	0.0002	0.0002
		(0.320)	(0.258)	(0.258)	(0.484)	(0.489)	(0.322)	(0.322)
bHML		0.0028**	0.0028**	0.0028**	0.0026**	0.0026**	0.0028**	0.0028**
		(2.462)	(2.466)	(2.467)	(2.338)	(2.336)	(2.453)	(2.450)
bSMB		0.0003	0.0003	0.0003	0.0001	0.0001	0.0003	0.0003
		(0.182)	(0.214)	(0.213)	(0.068)	(0.065)	(0.185)	(0.187)
LEVERAGE		0.0507***	0.0512***	0.0512***	0.0455***	0.0454***	0.0504***	0.0504***
		(6.256)	(6.292)	(6.291)	(5.282)	(5.270)	(6.064)	(6.055)
COEFVAR		0.0082*	0.0081*	0.0081*	0.0075	0.0075	0.0082*	0.0082*

		(1.773)	(1.768)	(1.768)	(1.613)	(1.609)	(1.770)	(1.770)
GROW		0.0006***	0.0006***	0.0006***	0.0006***	0.0006***	0.0006***	0.0006***
		(2.808)	(2.879)	(2.878)	(2.860)	(2.857)	(2.824)	(2.828)
N	679	679	679	679	679	679	679	679
Adj R^2	0.044	0.140	0.140	0.140	0.144	0.144	0.138	0.138

This table reports Ordinary Least Squares regression estimation results. The sample consists of 679 industry-year averages from 1990 to 2006.The dependent variable, r_{avg}, is the mean of the four estimated models for the implied cost of equity capital minus the 3-month treasury bill returns for June in year t. SENTIMENT is the natural log of Michigan Consumer Sentiment Index . Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 5B

Sentiment, Implied Cost of Equity and Synchronicity

VARIABLES	(9) r_{avg}	(10) r_{avg}	(11) r_{avg}	(12) r_{avg}	(13) r_{avg}	(14) r_{avg}	(15) r_{avg}
Constant	0.2626***	0.2732***	0.2830***	0.2936***	0.2829***	0.2897***	0.2829***
	(8.031)	(8.999)	(9.278)	(9.829)	(9.319)	(9.456)	(8.897)
SENTIMENT (S)	-0.0484***	-0.0506***	-0.0532***	-0.0558***	-0.0532***	-0.0546***	-0.0541***
	(-6.464)	(-7.219)	(-7.559)	(-8.094)	(-7.626)	(-7.818)	(-7.528)
S *x* LOW	-0.0007**						
	(-2.067)						
S *x* QT1		-0.0013***					
		(-2.788)					
S *x* QT2			-0.0001				0.0010*
			(-0.329)				(1.767)
S *x* QT3				0.0014***			0.0022***
				(3.580)			(3.838)
S *x* QT4					0.0002		0.0012**
					(0.555)		(2.190)
S *x* QT5						-0.0002	0.0009
						(-0.561)	(1.527)
bMKT	0.0002	0.0001	0.0002	0.0001	0.0002	0.0002	0.0001
	(0.321)	(0.258)	(0.325)	(0.143)	(0.338)	(0.312)	(0.139)
bHML	0.0029**	0.0030***	0.0028**	0.0029**	0.0028**	0.0028**	0.0030***
	(2.578)	(2.713)	(2.456)	(2.515)	(2.448)	(2.436)	(2.669)
bSMB	0.0002	0.0001	0.0003	0.0005	0.0003	0.0003	0.0003
	(0.114)	(0.063)	(0.180)	(0.317)	(0.159)	(0.202)	(0.191)
LEV	0.0511***	0.0504***	0.0507***	0.0506***	0.0507***	0.0507***	0.0504***

	(6.229)	(6.276)	(6.251)	(6.389)	(6.262)	(6.287)	(6.404)
COEFVAR	0.0085*	0.0093**	0.0081*	0.0085*	0.0082*	0.0082*	0.0094**
	(1.864)	(2.139)	(1.760)	(1.869)	(1.787)	(1.771)	(2.142)
GROW	0.0006***	0.0006***	0.0006***	0.0006***	0.0006***	0.0006***	0.0006***
	(2.846)	(2.645)	(2.824)	(2.803)	(2.794)	(2.754)	(2.633)
N	679	679	679	679	679	679	679
Adj R^2	0.144	0.152	0.138	0.154	0.139	0.139	0.158

This table reports Ordinary Least Squares regression estimation results. The sample consists of 679 industry-year averages from 1990 to 2006. The dependent variable, r_{avg}, is the mean of the four estimated models for the implied cost of equity capital minus the 3-month treasury bill returns for June in year t. SENTIMENT is the natural log of Michigan Consumer Sentiment Index . Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 6A

Robustness Tests with Industry Fixed Effects

VARIABLES	(1) r_{avg}	(2) r_{avg}	(3) r_{avg}	(4) r_{avg}	(5) r_{avg}	(6) r_{avg}	(7) r_{avg}
Constant	0.2617***	0.2810***	0.2807***	0.2805***	0.2808***	0.2816***	0.2561***
	(12.107)	(12.648)	(12.648)	(12.630)	(12.658)	(12.704)	(10.738)
SENTIMENT (S)	-0.0421***	-0.0547***	-0.0546***	-0.0546***	-0.0547***	-0.0549***	-0.0492***
	(-8.823)	(-10.398)	(-10.370)	(-10.342)	(-10.400)	(-10.417)	(-8.733)
COMPETITIVE			-0.0009				
			(-0.374)				
S *x* COMPETITIVE				-0.0002			
				(-0.335)			
UNIQUE					0.0035		
					(0.777)		
S *x* UNIQUE						0.0007	
						(0.654)	
S *x* HIGH_TECH							-0.0439***
							(-3.205)
bMKT		0.0005	0.0005	0.0005	0.0005	0.0005	0.0005
		(1.086)	(1.102)	(1.100)	(1.074)	(1.073)	(1.001)
bHML		0.0019	0.0019	0.0019	0.0019	0.0019	0.0017
		(1.613)	(1.588)	(1.589)	(1.593)	(1.594)	(1.488)
bSMB		-0.0027*	-0.0027*	-0.0027*	-0.0027*	-0.0027*	-0.0025
		(-1.664)	(-1.672)	(-1.671)	(-1.647)	(-1.648)	(-1.566)
LEVERAGE		0.0534***	0.0532***	0.0532***	0.0535***	0.0535***	0.0512***
		(4.095)	(4.045)	(4.045)	(4.056)	(4.062)	(3.927)
COEFVAR		0.0119***	0.0119***	0.0119***	0.0119***	0.0119***	0.0125***
		(2.940)	(2.937)	(2.937)	(2.937)	(2.936)	(3.076)
GROW		0.0008***	0.0008***	0.0008***	0.0008***	0.0008***	0.0008***

		(3.172)	(3.150)	(3.152)	(3.142)	(3.147)	(3.417)
Industry Effects	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
N	679	679	679	679	679	679	679
Adj R^2	0.361	0.413	0.412	0.412	0.412	0.412	0.418

This table reports the results for Ordinary Least Squares regression estimation with industry dummies. The sample consists of 679 industry-year averages from 1990 to 2006. The dependent variable, $\boldsymbol{r_{avg}}$, is the mean of the four estimated models for the implied cost of equity capital minus the 3-month treasury bill returns for June in year t. SENTIMENT (S) is the natural log of Michigan Consumer Sentiment Index . Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 6B

Robustness Tests with Industry Fixed Effects

VARIABLES	(8) r_{avg}	(9) r_{avg}	(10) r_{avg}
Constant	0.2833***	0.2727***	0.2727***
	(10.872)	(11.072)	(11.072)
SENTIMENT (S)	-0.0555***	-0.0527***	-0.0530***
	(-8.518)	(-8.985)	(-9.247)
S *x* SYNCH	-0.0001		
	(-0.196)		
S *x* LOW		-0.0003	
		(-0.898)	
S *x* HIGH			0.0003
			(0.898)
bMKT	0.0005	0.0005	0.0005
	(1.065)	(1.118)	(1.118)
bHML	0.0019	0.0020*	0.0020*
	(1.604)	(1.667)	(1.667)
bSMB	-0.0027*	-0.0027*	-0.0027*
	(-1.650)	(-1.702)	(-1.702)
LEVERAGE	0.0534***	0.0536***	0.0536***
	(4.069)	(4.069)	(4.069)
COEFVAR	0.0119***	0.0118***	0.0118***
	(2.928)	(2.941)	(2.941)
GROW	0.0008***	0.0008***	0.0008***
	(3.188)	(3.148)	(3.148)
Industry Effects	**Yes**	**Yes**	**Yes**
N	679	679	679
Adj R^2	0.412	0.412	0.412

This table reports the results for Ordinary Least Squares regression estimation with industry dummies. The sample consists of 679 industry-year averages from 1990 to 2006. The dependent variable, r_{avg}, is the mean of the four estimated models for the implied cost of equity capital minus the 3-month treasury bill returns for June in year t. SENTIMENT (S) is the natural log of Michigan Consumer Sentiment Index . Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 7A

Robustness Tests with Sentiment and Raw Industry Cost of Equity Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**k**	**k**	**k**	**k**	**k**	**k**	**k**	**K**
Constant	0.1961***	0.2060***	0.2057***	0.2062***	0.2041***	0.2028***	0.2058***	0.2057***
	(6.348)	(6.739)	(6.733)	(6.752)	(6.730)	(6.686)	(6.736)	(6.726)
SENTIMENT (S)	-0.0184***	-0.0268***	-0.0270***	-0.0271***	-0.0256***	-0.0253***	-0.0267***	-0.0267***
	(-2.677)	(-3.775)	(-3.806)	(-3.821)	(-3.636)	(-3.589)	(-3.757)	(-3.747)
COMPETITIVE			0.0021					
			(1.344)					
S *x* COMPETITIVE				0.0005				
				(1.326)				
UNIQUE					-0.0043**			
					(-2.507)			
S *x* UNIQUE						-0.0010**		
						(-2.533)		
HIGH_TECH							-0.0011	
							(-0.631)	
S *x* HIGH_TECH								-0.0003
								(-0.723)
bMKT		-0.0009*	-0.0009**	-0.0009**	-0.0008*	-0.0008*	-0.0009*	-0.0009*
		(-1.921)	(-2.039)	(-2.038)	(-1.743)	(-1.739)	(-1.895)	(-1.892)
bHML		-0.0004	-0.0004	-0.0004	-0.0006	-0.0006	-0.0004	-0.0004
		(-0.450)	(-0.497)	(-0.494)	(-0.743)	(-0.745)	(-0.488)	(-0.494)
bSMB		0.0043***	0.0044***	0.0044***	0.0041***	0.0041***	0.0044***	0.0044***
		(3.881)	(3.966)	(3.963)	(3.779)	(3.776)	(3.872)	(3.874)
LEVERAGE		0.0510***	0.0517***	0.0517***	0.0450***	0.0449***	0.0503***	0.0502***
		(7.167)	(7.225)	(7.223)	(5.906)	(5.893)	(6.920)	(6.908)
COEFVAR		0.0052	0.0051	0.0051	0.0045	0.0045	0.0053	0.0053

		(1.441)	(1.439)	(1.439)	(1.246)	(1.243)	(1.444)	(1.446)
GROW		0.0004**	0.0004**	0.0004**	0.0004**	0.0004**	0.0004**	0.0004**
		(1.974)	(2.080)	(2.079)	(2.017)	(2.014)	(2.013)	(2.018)
N	679	679	679	679	679	679	679	679
Adj R^2	0.011	0.113	0.114	0.114	0.121	0.121	0.112	0.112

This table reports the results for Ordinary Least Squares regression estimation. The sample consists of 679 industry-year averages from 1990 to 2006. The dependent variable, k, is the mean of the four estimated models for the implied cost of equity capital. SENTIMENT (S) is the natural log of Michigan Consumer Sentiment Index . Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 7B

Robustness Tests with Sentiment and Raw Industry Cost of Equity Estimates

VARIABLES	(9) k	(10) k	(11) k
Constant	0.1663***	0.1780***	0.1780***
	(5.122)	(5.475)	(5.475)
SENTIMENT (S)	-0.0152**	-0.0202***	-0.0212***
	(-1.969)	(-2.687)	(-2.852)
S *x* SYNCH	0.0014***		
	(3.399)		
S *x* LOW		-0.0009***	
		(-2.906)	
S *x* HIGH			0.0009***
			(2.906)
bMKT	-0.0008**	-0.0009**	-0.0009**
	(-1.993)	(-2.024)	(-2.024)
bHML	-0.0001	-0.0003	-0.0003
	(-0.130)	(-0.319)	(-0.319)
bSMB	0.0039***	0.0042***	0.0042***
	(3.524)	(3.804)	(3.804)
LEVERAGE	0.0502***	0.0516***	0.0516***
	(6.945)	(7.162)	(7.162)
COEFVAR	0.0065*	0.0057	0.0057
	(1.830)	(1.582)	(1.582)
GROW	0.0004*	0.0004**	0.0004**
	(1.907)	(2.055)	(2.055)
N	679	679	679
Adj R^2	0.136	0.124	0.124

This table reports the results for Ordinary Least Squares regression estimation. The sample consists of 679 industry-year averages from 1990 to 2006. The dependent variable, k, is the mean of the four estimated models for the implied cost of equity capital. SENTIMENT (S) is the natural log of Michigan Consumer Sentiment Index . Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 8

Robustness Tests with Lagged Sentiment and Industry Cost of Equity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	r_{avg}	r_{avg}	r_{avg}	r_{avg}	r_{avg}	r_{avg}	r_{avg}
Constant	0.1505***	0.1538***	0.1493***	0.1305***	0.1363***	0.1363***	0.1503***
	(4.704)	(4.761)	(4.653)	(3.694)	(4.030)	(4.030)	(4.695)
LAG_SENTIMENT (S)	-0.0227***	-0.0234***	-0.0214***	-0.0164*	-0.0193**	-0.0198***	-0.0226***
	(-3.090)	(-3.162)	(-2.893)	(-1.960)	(-2.500)	(-2.599)	(-3.074)
S *x* COMPETITIVE		0.0003					
		(0.795)					
S *x* UNIQUE			-0.0011**				
			(-2.524)				
S *x* SYNCH				0.0009*			
				(1.778)			
S *x* LOW					-0.0005		
					(-1.392)		
S *x* HIGH						0.0005	
						(1.392)	
S *x* HIGH_TECH							-0.0001
							(-0.303)
bMKT	0.0003	0.0005	0.0006	0.0004	0.0003	0.0003	0.0003
	(0.713)	(0.980)	(1.181)	(0.841)	(0.665)	(0.665)	(0.714)
bHML	0.0021*	0.0026**	0.0023*	0.0028**	0.0021*	0.0021*	0.0021*
	(1.887)	(2.049)	(1.901)	(2.211)	(1.919)	(1.919)	(1.870)
bSMB	0.0003	-0.0003	-0.0005	-0.0005	0.0003	0.0003	0.0003
	(0.189)	(-0.210)	(-0.327)	(-0.296)	(0.182)	(0.182)	(0.197)
LEVERAGE	0.0452***	0.0435***	0.0363***	0.0425***	0.0457***	0.0457***	0.0448***
	(5.699)	(5.304)	(4.219)	(5.154)	(5.676)	(5.676)	(5.494)

COEFVAR	0.0091*	0.0085*	0.0076	0.0089*	0.0093*	0.0093*	0.0092*
	(1.850)	(1.727)	(1.526)	(1.894)	(1.903)	(1.903)	(1.846)
GROW	0.0004*	0.0004*	0.0004*	0.0004*	0.0004*	0.0004*	0.0004*
	(1.798)	(1.870)	(1.797)	(1.750)	(1.806)	(1.806)	(1.822)
N	678	636	636	636	678	678	678
Adj R^2	0.079	0.076	0.084	0.082	0.080	0.080	0.078

This table reports the results for Ordinary Least Squares regression estimation with industry dummies. The dependent variable, ravg, is the mean of the four estimated models for the implied cost of equity capital minus the 3-month treasury bill returns for June in year t. LAG_SENTIMENT (S) is the lagged value of the natural log of Michigan Consumer Sentiment Index . All interaction terms are calculated with the respective lagged test variable. Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 9A

Robustness Tests with Sentiment Measured in June

VARIABLES	(1) r_{avg}	(2) r_{avg}	(3) r_{avg}	(4) r_{avg}	(5) r_{avg}	(6) r_{avg}	(7) r_{avg}	(8) r_{avg}
Constant	0.3165***	0.3721***	0.3719***	0.3723***	0.3693***	0.3682***	0.3721***	0.3720***
	(8.609)	(9.939)	(9.927)	(9.942)	(9.964)	(9.933)	(9.930)	(9.926)
SENTIMENT$_{JUNE}$ (S$_{JUNE}$)	-0.0536***	-0.0732***	-0.0733***	-0.0734***	-0.0719***	-0.0716***	-0.0732***	-0.0731***
	(-6.593)	(-8.490)	(-8.507)	(-8.519)	(-8.432)	(-8.395)	(-8.473)	(-8.467)
COMPETITIVE			0.0017					
			(1.043)					
S$_{JUNE}$ *x* COMPETITIVE				0.0004				
				(1.045)				
UNIQUE					-0.0036**			
					(-1.987)			
S$_{JUNE}$ *x* UNIQUE						-0.0008**		
						(-2.004)		
HIGH_TECH							-0.0003	
							(-0.164)	
S$_{JUNE}$ *x* HIGH_TECH								-0.0001
								(-0.207)
bMKT		0.0001	0.0001	0.0001	0.0002	0.0002	0.0001	0.0001
		(0.224)	(0.162)	(0.162)	(0.384)	(0.387)	(0.225)	(0.226)
bHML		0.0028**	0.0028**	0.0028**	0.0026**	0.0026**	0.0028**	0.0028**
		(2.508)	(2.508)	(2.508)	(2.385)	(2.384)	(2.501)	(2.499)
bSMB		0.0004	0.0005	0.0005	0.0002	0.0002	0.0004	0.0004
		(0.269)	(0.301)	(0.300)	(0.158)	(0.155)	(0.272)	(0.273)
LEVERAGE		0.0537***	0.0542***	0.0542***	0.0486***	0.0486***	0.0535***	0.0534***

		(6.569)	(6.601)	(6.600)	(5.570)	(5.564)	(6.353)	(6.348)
COEFVAR		0.0083*	0.0082*	0.0082*	0.0077*	0.0077*	0.0083*	0.0083*
		(1.841)	(1.837)	(1.837)	(1.680)	(1.678)	(1.838)	(1.839)
GROW		0.0007***	0.0007***	0.0007***	0.0007***	0.0007***	0.0007***	0.0007***
		(3.145)	(3.209)	(3.209)	(3.197)	(3.195)	(3.165)	(3.168)
N	679	679	679	679	679	679	679	679
Adj R^2	0.052	0.154	0.154	0.154	0.158	0.158	0.153	0.153

This table reports the results for Ordinary Least Squares regression estimation. The dependent variable, $\boldsymbol{r_{avg}}$, is the mean of the four estimated models for the implied cost of equity capital minus the 3-month treasury bill returns for June in year t. $\text{SENTIMENT}_{\text{JUNE}}$ is the natural log of Michigan Consumer Sentiment Index in June of year t . Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 9B

Robustness Tests with Sentiment Measured in June

VARIABLES	(9) r_{avg}	(10) r_{avg}	(11) r_{avg}
Constant	0.3591***	0.3490***	0.3490***
	(8.562)	(8.348)	(8.348)
SENTIMENT$_{JUNE}$ (S$_{JUNE}$)	-0.0696***	-0.0678***	-0.0684***
	(-7.054)	(-7.102)	(-7.274)
S$_{JUNE}$ x SYNCH	0.0003		
	(0.702)		
S$_{JUNE}$ x LOW		-0.0005	
		(-1.477)	
S$_{JUNE}$ x HIGH			0.0005
			(1.477)
bMKT	0.0001	0.0001	0.0001
	(0.250)	(0.231)	(0.231)
bHML	0.0029***	0.0029***	0.0029***
	(2.602)	(2.591)	(2.591)
bSMB	0.0003	0.0003	0.0003
	(0.201)	(0.215)	(0.215)
LEVERAGE	0.0534***	0.0537***	0.0537***
	(6.559)	(6.531)	(6.531)
COEFVAR	0.0086*	0.0086*	0.0086*
	(1.929)	(1.903)	(1.903)
GROW	0.0007***	0.0007***	0.0007***
	(3.132)	(3.145)	(3.145)
N	679	679	679
Adj R^2	0.154	0.156	0.156

This table reports the results for Ordinary Least Squares regression estimation. The dependent variable, r_{avg}, is the mean of the four estimated models for the implied cost of equity capital minus the 3-month treasury bill returns for June in year t. SENTIMENT$_{JUNE}$ is the natural log of Michigan Consumer Sentiment Index in June of year t. Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 10

Robustness Tests with Baker and Wurgler's Sentiment Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	r_{avg}	r_{avg}	r_{avg}	r_{avg}	r_{avg}	r_{avg}	r_{avg}	r_{avg}	r_{avg}
Constant	0.0463***	0.0454***	0.0463***	0.0498***	0.0464***	0.0465***	0.0461***	0.0462***	0.0459***
	(8.088)	(7.768)	(8.079)	(8.460)	(8.099)	(8.031)	(8.039)	(8.049)	(7.989)
$\boldsymbol{SENTIMENT_{BW}}$ $(\boldsymbol{S_{BW}})$	-0.0060***	-0.0060***	-0.0061***	-0.0058***	-0.0052***	-0.0060***	-0.0054***	-0.0076	-0.0052***
	(-4.511)	(-4.523)	(-3.948)	(-4.401)	(-3.122)	(-4.505)	(-3.728)	(-1.441)	(-2.984)
COMPETITIVE		0.0017							
		(0.967)							
$\boldsymbol{S_{BW}\ x}$ **COMP**			0.0006						
			(0.218)						
UNIQUE				-0.0042**					
				(-2.313)					
$\boldsymbol{S_{BW}\ x}$ **UNIQ**					-0.0027				
					(-1.112)				
HIGH_TECH						-0.0006			
						(-0.285)			
$\boldsymbol{S_{BW}\ x}$ **HIGH_TECH**							-0.0048		
							(-1.561)		
$\boldsymbol{S_{BW}\ x}$ **SYNCH**								-0.0008	
								(-0.291)	
$\boldsymbol{S_{BW}\ x}$ **HIGH**									-0.0022
									(-0.751)
bMKT	0.0004	0.0003	0.0004	0.0005	0.0004	0.0004	0.0003	0.0004	0.0003
	(0.761)	(0.709)	(0.760)	(0.939)	(0.789)	(0.762)	(0.706)	(0.748)	(0.720)
bHML	0.0021*	0.0020*	0.0021*	0.0019*	0.0021*	0.0021*	0.0020*	0.0021*	0.0021*
	(1.854)	(1.849)	(1.851)	(1.693)	(1.860)	(1.839)	(1.778)	(1.859)	(1.847)
bSMB	0.0003	0.0004	0.0003	0.0001	0.0003	0.0003	0.0004	0.0003	0.0004

	(0.217)	(0.248)	(0.216)	(0.084)	(0.185)	(0.223)	(0.281)	(0.224)	(0.249)
LEVERAGE	0.0472***	0.0477***	0.0472***	0.0414***	0.0467***	0.0468***	0.0470***	0.0471***	0.0470***
	(6.097)	(6.130)	(6.097)	(5.079)	(6.026)	(5.897)	(6.080)	(6.084)	(6.104)
COEFVAR	0.0094**	0.0094**	0.0094**	0.0087*	0.0094**	0.0095**	0.0095**	0.0094**	0.0095**
	(2.035)	(2.037)	(2.040)	(1.855)	(1.993)	(2.031)	(2.029)	(2.001)	(2.024)
GROW	0.0005**	0.0005**	0.0005**	0.0005**	0.0005**	0.0005**	0.0005**	0.0005**	0.0005**
	(2.188)	(2.253)	(2.184)	(2.227)	(2.210)	(2.212)	(2.269)	(2.206)	(2.240)
N	679	679	679	679	679	679	679	679	679
Adj R^2	0.098	0.098	0.097	0.103	0.098	0.097	0.099	0.097	0.097

This table reports the results for Ordinary Least Squares regression estimation. The dependent variable, ravg, is the mean of the four estimated models for the implied cost of equity capital minus the 3-month treasury bill returns for June in year t. $SENTIMENT_{BW}$ (S_{BW}) is Baker and Wurgler's composite sentiment index. Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 11

Robustness Tests with Claus and Thomas (2001) Cost of Equity Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	k_{CT}	k_{CT}	k_{CT}	k_{CT}	k_{CT}	k_{CT}	k_{CT}	k_{CT}
Constant	0.1805***	0.1841***	0.1843***	0.1840***	0.1820***	0.1804***	0.1829***	0.1739***
	(4.848)	(5.510)	(5.510)	(5.510)	(5.466)	(5.409)	(5.513)	(4.754)
SENTIMENT (S)	-0.0166**	-0.0234***	-0.0233***	-0.0232***	-0.0220***	-0.0216***	-0.0228***	-0.0210**
	(-2.016)	(-3.089)	(-3.077)	(-3.069)	(-2.891)	(-2.833)	(-3.029)	(-2.578)
COMPETITIVE			-0.0012					
			(-0.669)					
S x COMPETITIVE				-0.0003				
				(-0.674)				
UNIQUE					-0.0051**			
					(-2.523)			
S x UNIQUE						-0.0012**		
						(-2.579)		
S x HIGH_TECH							-0.0012**	
							(-2.463)	
S x LOW								-0.0017
								(-0.938)
bMKT		-0.0007	-0.0007	-0.0007	-0.0006	-0.0006	-0.0007	-0.0007
		(-1.562)	(-1.506)	(-1.506)	(-1.339)	(-1.333)	(-1.469)	(-1.587)
bHML		-0.0010	-0.0010	-0.0010	-0.0013	-0.0013	-0.0011	-0.0009
		(-1.045)	(-1.017)	(-1.018)	(-1.416)	(-1.422)	(-1.221)	(-1.002)
bSML		0.0051***	0.0050***	0.0050***	0.0048***	0.0048***	0.0052***	0.0050***
		(3.915)	(3.909)	(3.908)	(3.766)	(3.762)	(3.924)	(3.850)
LEVERAGE		0.0403***	0.0399***	0.0399***	0.0332***	0.0330***	0.0368***	0.0405***
		(4.054)	(3.960)	(3.959)	(3.042)	(3.031)	(3.578)	(4.030)
COEFVAR		0.0067	0.0067	0.0067	0.0058	0.0058	0.0070	0.0069

		(0.487)	(0.489)	(0.489)	(0.427)	(0.426)	(0.508)	(0.502)
GROW		0.0005*	0.0005*	0.0005*	0.0005*	0.0005*	0.0006*	0.0005*
		(1.737)	(1.660)	(1.660)	(1.765)	(1.763)	(1.871)	(1.745)
N	679	679	679	679	679	679	679	679
Adj R^2	0.005	0.059	0.058	0.058	0.066	0.066	0.063	0.058

This table reports Ordinary Least Squares regression estimation results. The sample consists of 679 industry-year averages from 1990 to 2006.The dependent variable, k_{CT} , is the implied cost of equity capital estimate based on Claus and Thomas (2001). SENTIMENT is the natural log of Michigan Consumer Sentiment Index . Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 12

Robustness Tests with Easton (2004) Cost of Equity Estimates

VARIABLES	(1) k_{ES}	(2) k_{ES}	(3) k_{ES}	(4) k_{ES}	(5) k_{ES}	(6) k_{ES}	(7) k_{ES}	(8) k_{ES}
Constant	0.2295***	0.2535***	0.2529***	0.2541***	0.2503***	0.2481***	0.2537***	0.2138***
	(6.075)	(6.624)	(6.642)	(6.675)	(6.639)	(6.567)	(6.610)	(5.290)
SENTIMENT (S)	-0.0227***	-0.0369***	-0.0373***	-0.0376***	-0.0347***	-0.0342***	-0.0369***	-0.0275***
	(-2.711)	(-4.132)	(-4.206)	(-4.236)	(-3.950)	(-3.880)	(-4.120)	(-2.937)
COMPETITIVE			0.0050**					
			(2.507)					
S *x* COMPETITIVE				0.0011**				
				(2.480)				
UNIQUE					-0.0076***			
					(-3.843)			
S *x* UNIQUE						-0.0017***		
						(-3.860)		
S *x* HIGH_TECH							0.0001	
							(0.291)	
S *x* LOW								-0.0013***
								(-3.366)
bMKT		-0.0013**	-0.0014**	-0.0014**	-0.0012**	-0.0012**	-0.0013**	-0.0013**
		(-2.276)	(-2.521)	(-2.518)	(-2.040)	(-2.038)	(-2.287)	(-2.395)
bHML		0.0009	0.0008	0.0008	0.0005	0.0005	0.0009	0.0011
		(0.775)	(0.729)	(0.732)	(0.434)	(0.434)	(0.792)	(0.938)
bSML		0.0050***	0.0052***	0.0052***	0.0047***	0.0047***	0.0050***	0.0048***
		(3.392)	(3.559)	(3.554)	(3.263)	(3.260)	(3.377)	(3.299)
LEVERAGE		0.0628***	0.0644***	0.0644***	0.0523***	0.0522***	0.0632***	0.0636***
		(6.588)	(6.753)	(6.750)	(5.205)	(5.194)	(6.458)	(6.590)
COEFVAR		0.0157**	0.0155**	0.0155**	0.0144**	0.0144**	0.0156**	0.0163***

		(2.482)	(2.539)	(2.540)	(2.252)	(2.250)	(2.478)	(2.623)
GROW		0.0007***	0.0008***	0.0008***	0.0007***	0.0007***	0.0007***	0.0008***
		(2.990)	(3.213)	(3.210)	(3.075)	(3.069)	(2.986)	(3.098)
N	679	679	679	679	679	679	679	679
Adj R^2	0.010	0.127	0.134	0.134	0.143	0.144	0.126	0.140

This table reports Ordinary Least Squares regression estimation results. The sample consists of 679 industry-year averages from 1990 to 2006.The dependent variable, k_{ES} , is the implied cost of equity capital estimate based on Easton (2004). SENTIMENT is the natural log of Michigan Consumer Sentiment Index . Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 13

Robustness Tests with Ohlson and Juettner-Nauroth (2005) Cost of Equity Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	k_{OJ}	k_{OJ}	k_{OJ}	k_{OJ}	k_{OJ}	k_{OJ}	k_{OJ}	k_{OJ}
Constant	0.2983***	0.3188***	0.3181***	0.3194***	0.3157***	0.3136***	0.3190***	0.2781***
	(7.612)	(8.007)	(8.042)	(8.073)	(8.020)	(7.949)	(7.987)	(6.669)
SENTIMENT (S)	-0.0362***	-0.0502***	-0.0507***	-0.0510***	-0.0482***	-0.0477***	-0.0504***	-0.0407***
	(-4.173)	(-5.418)	(-5.502)	(-5.531)	(-5.248)	(-5.178)	(-5.401)	(-4.198)
COMPETITIVE			0.0051**					
			(2.453)					
S *x* COMPETITIVE				0.0011**				
				(2.430)				
UNIQUE					-0.0072***			
					(-3.463)			
S *x* UNIQUE						-0.0016***		
						(-3.476)		
S *x* HIGH_TECH							0.0002	
							(0.437)	
S *x* LOW								-0.0014***
								(-3.311)
bMKT		-0.0016**	-0.0016***	-0.0016***	-0.0014**	-0.0014**	-0.0016**	-0.0016***
		(-2.563)	(-2.812)	(-2.809)	(-2.343)	(-2.341)	(-2.583)	(-2.698)
bHML		0.0001	0.0000	0.0001	-0.0003	-0.0003	0.0002	0.0003
		(0.110)	(0.041)	(0.045)	(-0.238)	(-0.238)	(0.136)	(0.264)
bSML		0.0058***	0.0059***	0.0059***	0.0054***	0.0054***	0.0057***	0.0056***
		(3.874)	(4.045)	(4.040)	(3.753)	(3.751)	(3.859)	(3.783)
LEVERAGE		0.0646***	0.0662***	0.0662***	0.0545***	0.0544***	0.0652***	0.0654***
		(6.549)	(6.713)	(6.710)	(5.218)	(5.208)	(6.441)	(6.549)
COEFVAR		0.0182***	0.0180***	0.0180***	0.0170***	0.0170***	0.0182***	0.0189***

		(2.831)	(2.909)	(2.910)	(2.628)	(2.626)	(2.831)	(2.972)
GROW		0.0009***	0.0009***	0.0009***	0.0009***	0.0009***	0.0008***	0.0009***
		(3.335)	(3.568)	(3.564)	(3.402)	(3.397)	(3.321)	(3.445)
N	679	679	679	679	679	679	679	679
Adj R^2	0.025	0.138	0.144	0.144	0.151	0.151	0.137	0.150

This table reports Ordinary Least Squares regression estimation results. The sample consists of 679 industry-year averages from 1990 to 2006.The dependent variable, k_{OJ} , is the implied cost of equity capital estimate based on Ohlson and Juettner-Nauroth (2005) minus the 3-month treasury bill returns for June in year t. SENTIMENT is the natural log of Michigan Consumer Sentiment Index . Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

Table 14

Robustness Tests with Gebhardt et al. (2001) Cost of Equity Estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	k_{GLS}	k_{GLS}	k_{GLS}	k_{GLS}	k_{GLS}	k_{GLS}	k_{GLS}	k_{GLS}
Constant	0.0761**	0.0674**	0.0674**	0.0673**	0.0685**	0.0693**	0.0671**	0.0462
	(2.262)	(2.134)	(2.136)	(2.130)	(2.188)	(2.222)	(2.126)	(1.290)
SENTIMENT (S)	0.0020	0.0033	0.0034	0.0034	0.0026	0.0024	0.0035	0.0083
	(0.273)	(0.462)	(0.466)	(0.468)	(0.361)	(0.341)	(0.480)	(1.013)
COMPETITIVE			-0.0005					
			(-0.337)					
S *x* COMPETITIVE				-0.0001				
				(-0.325)				
UNIQUE					0.0028			
					(1.381)			
S *x* UNIQUE						0.0006		
						(1.329)		
S *x* HIGH_TECH							-0.0003	
							(-0.889)	
S *x* LOW								-0.0007**
								(-1.976)
bMKT		0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
		(0.339)	(0.355)	(0.354)	(0.187)	(0.190)	(0.346)	(0.343)
bHML		-0.0017***	-0.0017***	-0.0017***	-0.0015**	-0.0015**	-0.0017***	-0.0016***
		(-2.661)	(-2.618)	(-2.620)	(-2.359)	(-2.367)	(-2.728)	(-2.621)
bSML		0.0015	0.0015	0.0015	0.0016	0.0016	0.0015	0.0014
		(1.301)	(1.275)	(1.276)	(1.478)	(1.475)	(1.317)	(1.230)
LEVERAGE		0.0363***	0.0362***	0.0362***	0.0402***	0.0401***	0.0356***	0.0368***
		(6.562)	(6.453)	(6.452)	(6.299)	(6.282)	(6.274)	(6.594)
COEFVAR		-0.0197***	-0.0197***	-0.0197***	-0.0192***	-0.0192***	-0.0196***	-0.0193***

		(-4.408)	(-4.411)	(-4.411)	(-4.364)	(-4.363)	(-4.407)	(-4.392)
GROW		-0.0006***	-0.0006***	-0.0006***	-0.0006***	-0.0006***	-0.0006***	-0.0006***
		(-2.994)	(-2.937)	(-2.935)	(-2.989)	(-2.988)	(-2.956)	(-3.003)
N	679	679	679	679	679	679	679	679
Adj R^2	-0.001	0.154	0.153	0.153	0.156	0.156	0.153	0.159

This table reports Ordinary Least Squares regression estimation results. The sample consists of 679 industry-year averages from 1990 to 2006.The dependent variable, k_{GLS}, is the implied cost of equity capital estimate based on Gebhardt et al. (2001). SENTIMENT is the natural log of Michigan Consumer Sentiment Index . Numbers in parentheses are t-statistics calculated with heteroscedastic robust standard errors. ***, **, and * represent statistical significance at 1%, 5% and 10% significance level respectively. Refer to Appendix A for variables description.

APPENDIX A

Variables Description

Variable	Description	Data Source
Dependent Variables		
k_{GLS}	Cost of equity derived from the Gebhardt, Lee, and Swaminathan (2001) model estimated in June of each year	Calculated estimate based on I/B/E/S and Research Insight /Compustat
k_{OJ}	Cost of equity derived from the Ohlson and Juttner-Nauroth (2005) model estimated in June of each year	Calculated estimate based on I/B/E/S and Research Insight /Compustat
k_{CT}	Cost of equity derived from the Claus and Thomas (2001) model estimated in June of each year	Calculated estimate based on I/B/E/S and Research Insight /Compustat
k_{ES}	Cost of equity defined derived from the Easton (2004) model estimated in June of each year	Calculated estimate based on I/B/E/S and Research Insight /Compustat
k_{avg}	Industry average of the above four estimates across all Fama and French (1997) industry classification, excluding financial industries	Calculated estimate based on I/B/E/S and Research Insight /Compustat
r_{avg}	Industry average equity risk premium calculates as k_{avg} minus the rate of the 3-month US Treasury Bill	Calculated estimate based on I/B/E/S and Research Insight /Compustat
Test Variables		
$SENTIMENT$ (S)	Natural logarithm of the Michigan Consumer Confidence Index	Federal Reserve Economic Data
$SENTIMENT_{BW}$	Baker and Wurgler (2006) composite sentiment index	Jeffrey Wurgler official website
$SYNCH$	Synchronicity measure, proxy for information availability. Measured as a logarithmic transformation of the industry average R^2 from the	CRSP

	market model: $SYNCH = \ln\left(\frac{R_I^2}{1-R_I^2}\right)$.	
$UNIQUE$	Unique industry dummy variable: 1 if the industry is in the bottom quartile of all 48 Fama-French industries annually sorted by the industry-median product uniqueness, 0 otherwise. Product uniqueness is defined as selling expenses scaled by sales.	Masulis et al. (2007) Research Insight /Compustat
$COMPETITIVE$	Competitive industry dummy variable: 1 if the industry is in the bottom quartile of all 48 Fama-French industries annually sorted by the Herfindahl index, 0 otherwise.	Masulis et al. (2007) Research Insight /Compustat
$HERFINDAHL$ $INDEX$	The sum of squared market shares of all Compustat firms in the industry with valid data on sales.	Research Insight /Compustat
$HIGH\_TECH$	High-tech industry dummy: 1 if the industry is defined as high-tech as in Grullon, Lyandres and Zhdanov (2010), 0 otherwise.	
$S\ x\ UNIQUE$	An interaction term between the Michigan Consumer Sentiment Index and the unique industry dummy variable	
$S\ x\ SYNCH$	An interaction term between the Michigan Consumer Sentiment Index and the synchronicity measure, proxy for information availability.	
$S\ x\ COMPETITIVE$	An interaction term between the Michigan Consumer Sentiment Index and the competitive industry dummy variable.	
LOW	Low R^2 industry dummy variable: 1 if SYNCH is below the median, 0 otherwise.	
$HIGH$	High R^2 industry dummy variable: 1 if SYNCH is above the median, 0 otherwise.	

$S \times LOW$	An interaction term between the Michigan Consumer Sentiment Index and the low R^2 industry dummy variable	
$S \times HIGH$	An interaction term between the Michigan Consumer Sentiment Index and the high R^2 industry dummy variable	
QT_i	A R^2 industry dummy variable identifying each quintile (i=1,2,3,4,5) sorted on SYNCH where QT_1 is the bottom quintile and QT_5 is the top quintile.	
$S \times QT_i$	An interaction term between the Michigan Consumer Sentiment Index and the corresponding industry SYNCH dummy variable	
$S \times HIGH\_TECH$	An interaction term between the Michigan Consumer Sentiment Index and the high-tech industry dummy variable	
Control Variables		
$bMKT$	Loading of excess equity returns in the market factor of the Fama and French (1993) three-factor model. A proxy for firm's market risk. Averaged over the Fama-French 48 industry groups.	Mamun and Mishra (2010)
$bSMB$	Loading of excess equity returns in the small minus big (SMB) factor of the Fama-French (1993) three-factor model. A proxy for the firm's size related risk. Averaged over the Fama-French 48 industry groups.	Mamun and Mishra (2010)
$bHML$	Loading of excess equity returns in the high market to book minus low market to book (HML) factor of the Fama-French (1993) three-factor model. A proxy for the firm's market to book value related risk. Averaged	Mamun and Mishra (2010)

	over the Fama-French 48 industry groups.	
$LEVERAGE$	Total Debt (Long Term debt plus Debt in Current Liabilities) divided by Total Invested Capital. Averaged over the Fama-French 48 industry groups.	Research Insight /Compustat
$COEFVAR$	Standard deviation of the estimated first year earnings per share divided by the mean earnings per share forecast for the first year. Averaged over the Fama-French 48 industry groups.	I/B/E/S
$GROW$	I/B/E/S five-year earnings growth rate where available, otherwise estimated as the growth in forecasted earnings from year 1 to year 3. Averaged over the Fama-French 48 industry groups.	I/B/E/S

APPENDIX B

Michigan Consumer Confidence Index

The following description of the Michigan Consumer Confidence Index borrows heavily from Thompson Reuters/University of Michigan Surveys of Consumers[11]. The index is part of a broader consumer survey conducted by the University of Michigan Survey Research Center, Institute for Social Research. The Index of Consumer Expectations, produced by the Surveys of Consumers, is included in the Leading Indicator Composite Index published by the U.S. Department of Commerce, Bureau of Economic Analysis. The Michigan index began as an annual survey in the late 1940s. In 1952, it was converted to a quarterly survey and in 1978 it started being conducted on a monthly basis.

The Survey of Consumers is a nationally representative survey based on approximately 500 telephone interviews with adult men and women living in households in the United States. The sample incorporates a rotating panel sample design in an ongoing monthly survey program. Each month, an independent cross section sample of households is drawn. The respondents chosen for the specific month are then reinterviewed six months later. The sample for each month contains up of 60% new respondents, and 40% interviewed for the second time. This approach enables regular assessment of change in attitudes and behaviour both at the aggregate and at the individual level. The survey methodology considers potential issues associated with demographic sampling, sampling error, sample coverage and nonresponse errors, telephone interviewing, coding methods, and institutional independence.

The Michigan Consumer Sentiment Index is based on the following five questions:

1. "We are interested in how people are getting along financially these days. Would you say that you (and your family living there) are better off or worse off financially than you were a year ago?"

2. "Now looking ahead—do you think that a year from now you (and your family living there) will be better off financially, or worse off, or just about the same as now?"

3. "Now turning to business conditions in the country as a whole—do you think that during the next twelve months we'll have good times financially, or bad times, or what?"

4. "Looking ahead, which would you say is more likely—that in the country as a whole we'll have continuous good times during the next five years or so, or that we will have periods of

[11] http://www.sca.isr.umich.edu/main.php

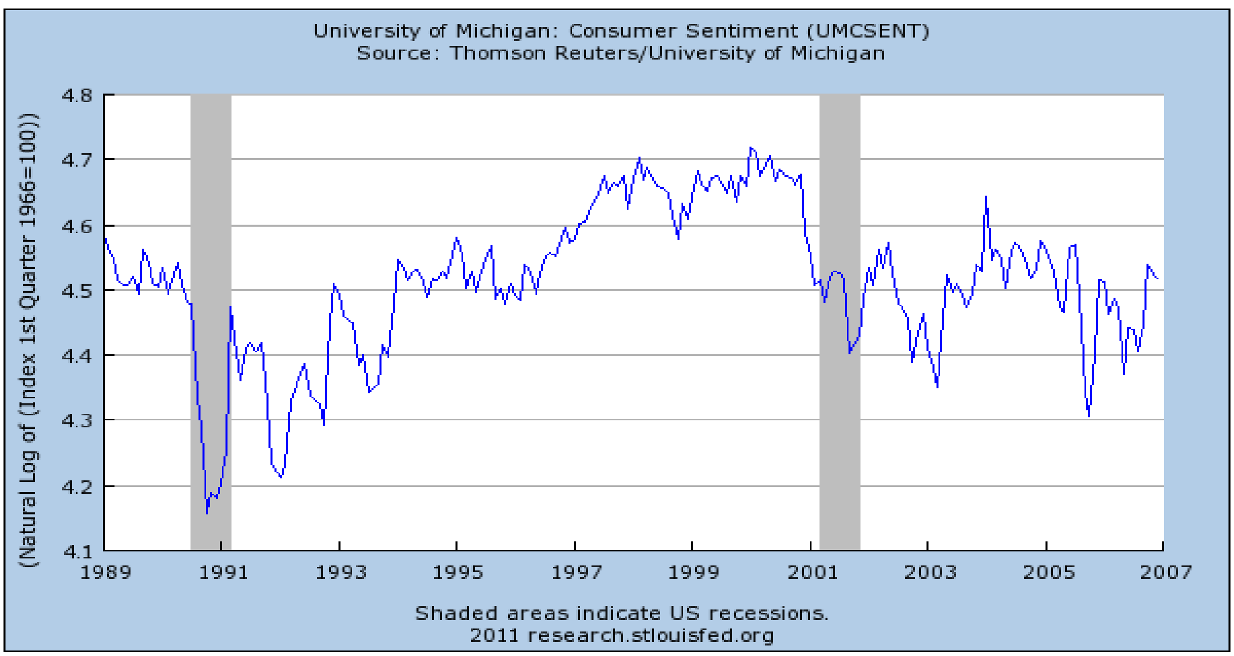
widespread unemployment or depression, or what?"

5. "About the big things people buy for their homes—such as furniture, a refrigerator, stove, television, and things like that. Generally speaking, do you think now is a good or bad time for people to buy major household items?"

The Index of Consumer Sentiment is calculated by first computing the relative scores (the percent giving favourable replies minus the percent giving unfavourable replies, plus 100) for each of the five survey questions. Each score is then rounded to the nearest whole number. The index is then constructed by summing the five relative scores (x_i) and dividing by the 1966 base period total of 6.7558, and adding 2. The reason for adding this constant is to correct for a sample design change from the 1950s.

$$S = \frac{x_1 + x_2 + x_3 + x_4 + x_5}{6.7558} + 2$$

The data series is not seasonally adjusted. The base period is the first quarter of 1966 = 100.



APPENDIX C

Models Used to Estimate the Cost of Equity Capital

This appendix provides information on the four models used to calculate the cost of equity estimates. First, we define variables common to all four models. Then we show assumptions and specifications associated with each separate model. The method of implementation of these estimates is based on Mamun and Mishra (2010).

The models mainly differ in regard to their assumptions about the long-term forecast horizon as well as the used earnings growth rate. Another, modification of each model is its assumptions about the growth rate beyond the terminal year (Guay et al., 2003).

$K_{subscript}$ = Cost of equity estimate of the model identified in the subscript. Cost of equity is computed as of the month of June of each firm year.

$FEPS_{t+\tau}$= I/B/E/S consensus earnings forecast per share for year $t+\tau$ recorded in June of the estimation year. $FEPS_1$ and $FEPS_2$ are equal to one and two-year ahead consensus earnings per share forecast reported in June of year *t*. $FEPS_3$ is equal to the three year-ahead consensus earnings per share forecast when available, and $FEPS_2$ ×(1+LTG) when not available.

P_t = I/B/E/S market price at the statistics release date for the estimation year

$D_{t+\tau}$ = $FEPS_{t+i}$ × Dividend Payout (firm's dividend payout, where available, otherwise 50% as in Claus and Thomas (2001), dividend payout is truncated at 50%)

EPS_t = earnings per share in year *t*

LTG= long-term growth forecast in the month cost of equity is being estimated of year *t*

$B_{t+\tau}$= book value per share for the estimation year calculated as: $B_{t+\tau}$=$B_{t+\tau-1}$+ $FEPS_{t+\tau} - D_{t+\tau}$.

r_f= yield on a US Treasury bond in June of year *t* minus 2%

Gebhardt, Lee, and Swaminathan (2001)

This model estimates the internal rate of return that equates the present value of expected future cash flows to the current stock price. The model assumes clean surplus accounting which allows the share price to be expresses in terms of forecasted returns on equity (ROE) and book values. $FROE_{t+4}$ to $FROE_{t+12}$ are forecasted such that ROE fades linearly to median industry ROE by *T* =

12. Year 12 residual income is earned in perpetuity assuming such rate is "value-neutral." The valuation equation is:

$$P_t = B_t + \sum_{\tau=1}^{11} \frac{FROE_{t+\tau} - k_{GLS}}{(1 + k_{GLS})} B_{t+\tau-1} + \frac{FROE_{t+12} - k_{GLS}}{k_{GLS}\,(1 + k_{GLS})^{11}} B_{t+11}.$$

$FROE_{t+\tau}$ = Forecasted Return on Equity for period t+τ. For years one through three this variable is equal to $FEPS_{t+\tau}/B_{t+\tau}$. Beyond year three $FROE_{t+\tau}$ is a linear interpolation to the industry median ROE.

$B_{t+\tau} = B_{t+\tau-1} + FROE_{t+\tau}(1 - D_{t+\tau})$.

Industry ROE is based on the Fama and French 48 Industry Classification. Growth in earnings after the 12th year is assumed to be zero. The cost of equity estimate is restricted between 0% and 100%.

Claus and Thomas (2001)

The model assumes clean surplus accounting, thus the firm value can be expressed in terms of accounting numbers relying on the same theory as the discounted valuation model. Explicit forecast horizon is set to 5 years. The forecast beyond two years are taken as reported by I/B/E/S where available. Otherwise they are generated based on the five-year consensus growth rate forecast or the average growth in $FEPS_1$ to $FEPS_3$. The long-term growth rate beyond five years g = annualized US Treasury Bond yield minus 2%. K_{CT} is restricted within 0–100%. Observations which do not converge are excluded.

$$P_t = B_t + \sum_{\tau=1}^{5} \frac{ae_{t+\tau}}{(1 + k_{CT})} + \frac{ae_{t+5}(1 + g)}{(k_{CT} - g)(1 + k_{CT})^5}$$

$$ae_{t+\tau} = FROE_{t+\tau} - k_{CT} B_{t+\tau-1}$$

$$B_{t+\tau-1} = B_{t+\tau} + FROE_{t+\tau}(1 - D_{t+\tau})$$

$$g = R_f - 0.02.$$

Ohlson and Juettner-Nauroth (2005)

We will follow Gode and Mohanram's (2003) implementation of the model. It is a generalization of the Gordon constant growth model. The explicit forecast horizon is set to 1 year. After that forecasted earnings grow at a near term rate (the average of the a percentage difference between the one year and two year ahead earnings forecasts, and the I/B/E/S long-term growth forecast), which is modeled as decaying to a perpetual rate (expected inflation rate). The dividend payout is assumed to be constant.

$$k_{OJ} = A + \sqrt{A^2 + \frac{FEPS_{t+1}}{P_t}(g_2 - (\gamma - 1))},$$

where

$$A = \frac{1}{2}\left[(\gamma - 1) + \frac{D_{t+1}}{P_t}\right]$$

$$STG = \frac{FEPS_{t+2} - FEPS_{t+1}}{FEPS_{t+1}}$$

$$g_2 = \frac{STG + LTG}{2}$$

$$\gamma - 1 = R_f - 0.02.$$

Easton (2004)

This model is a generalization of the Price-Earnings-Growth model and is based on Ohlson and Juettner-Nauroth's (2005) model. The explicit forecast horizon is set to 2 years. After that, forecasted abnormal earnings are assumed to grow in perpetuity at a constant rate. The valuation equation is as follows:

$$P_t = \frac{FEPS_{t+2} + k_{ES}DPS_{t+1} - FEPS_{t+1}}{k_{ES}^2}.$$

In order to avoid spurious results associated with the use of only one model, we adopt the Dhaliwal et al. (2006) and Boubakri et al. (2010) approach and compute the average cost of equity based on the four models. Then, we subtract the 3-month US Treasury bond yield from the estimated cost of equity which gives us the implied equity risk premium that we use as our dependent variable.